The Pennsylvania State University

The Graduate School

College of Education

A MODEL FOR PREDICTING PERFORMANCE IN INTRODUCTORY STATISTICS COURSES

A Thesis in

Instructional Systems

by

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Submitted in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

August 2006
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ABSTRACT

The purpose of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance. In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance.

This study uses existing data collected during Fall 2004 by the Pennsylvania State University’s center for teaching excellence on a statistics course that had been redesigned using innovative ways of teaching. A total of 249 students’ data were used in the analysis. Structural Equation Modeling (SEM) was the data analysis method used in this study to test for model fit, as well as to provide information on statistics performance through analysis of direct, indirect, and total effect.

The results from the confirmatory factor analysis supported the further use of the attitude and experience with group measurement model as a part of the ecological theory perspective of statistics performance model in addition to hypothesizing causal links among latent variables. The ecological theory perspective of statistics performance
model analysis suggested that the modified ecological model was an excellent explanation of the data. This suggests that statistics performance in the introductory statistics course could be predicted by the relationships among the four selected variables: attitude toward statistics, experience with group work, lab quizzes, and group projects.

The results showed that there was a significant and positive direct relationship between the individual factor-attitude toward statistics and statistics performance, but not an indirect relationship. In addition, there was a significant and positive indirect relationship between the interpersonal factor-experience with group work and statistics performance. However, an unexpected result in this study was the significant, negative direct effect of the experience of group work on statistics performance.

The current study contributes to the general understanding of statistics performance, which may be of interest to theorists and statistics instructors as they design their courses. Examination of varied relationships among attitudes toward statistics, experience of group work, and the reformed statistics course activities and statistics performance can also enhance the ecology perspective model of ecology development systems theories.
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ACKNOWLEDGEMENTS

I would like to thank to God almighty, who makes all things possible. This work would not have been possible if it were not for many special people in my life.

I would like to express my deep gratitude to Dr. Barbara Grabowski, my academic and thesis adviser, for her guidance throughout my doctoral work, especially this dissertation. She has taught me many lessons about being a good educator and a good researcher. I am very appreciative of her time and energy.

I am also grateful to Dr. William Harkness for his endless support, advice, and encouragement for this study. He has provided guidance and direction throughout this process, and I value his input and suggestions.

I wish to express my sincere appreciation and gratitude to my dissertation committee, Drs. Hoi Suen, Kyle Peck, and Pui-Wa Lei, for their guidance, direction, and inspiration. Having such a strong group of academics with a wealth of knowledge and insights about research has built my confidence throughout this work.

My heartfelt appreciation goes out to Dr. Jill Lane, my supervisor, for her endless care and guidance. She has been dedicated to helping me develop as a professional. Her encouragement, invaluable academic advising, and mentoring mean a lot to me.

I would like to express my sincere thanks to my former advisers in Korea, Drs. Hyung Huh, Ki-Jung Kim, Ki-Sub Yu, and Sung-Youn Hong who have motivated and guided me in my professional development.
There are also wonderfully supportive colleagues throughout my program and the course of this study, especially Heather McKinney, KyoungNa Kim, Steven McGriff, and Dr. Valerie Dudley for their friendship and prayers; Jiyeon Ryu, Dr. Yong Shik Kim, and Dr. Younghoon Kim, for their support and friendship; and Charles Brua for his editorial assistance. There are many others who, while unnamed, have contributed to this work in some way or another. My hope is that these individuals know that they have my thanks.

Finally, I thank my family most of all. To my father in heaven, my mom, Mungja Song, sister, Junghee, and brothers, Yonghwan and Jihwan—this work could not have been completed without their love, understanding, and confidence in me from thousands of miles away. My sincere thanks goes to Karen and Charles English for their support and love; they have been my parents during my time in the United States. My special thanks go to Jeon Ho Choi, for accompanying me through the final dissertation stage, for sharing my stresses and frustrations, and for his love and prayers.
Chapter 1

INTRODUCTION

Background

Over the last several years there has been an emerging body of research on the nature of university restructuring and its effects on learning. The Boyer Commission (1998), the National Council for the Accreditation of Teacher Education (2000), and the Interstate New Teacher and Assessment Support Consortium (1992) have recommended new approaches to teaching and learning for institutions of higher education. These professional groups specifically support instructional strategies that promote active learning, problem solving, hands-on experiences, group work, and innovative uses of technology (Millis & Cottell, 1998). The Boyer Commission and other educational panels note that education should produce graduates who can think critically, solve problems, and work in teams (National Evaluation Systems, 1997; National Goals Education Panel, 1992; The Boyer Commission, 1998). Thus, education should bridge the gap between education and practice (Cockrell et al., 2000) and capitalize on its potential to help improve educational outcomes (Major, 1999; Major & Eck, 2000; Major & Palmer, 2001).

Considering changes in learning and teaching from the constructivist learning and social psychological perspective, faculty members offer a learner-centered, hands-on learning environment to help students learn. In addition, there is a general movement to
develop innovative learning environments to help students make a smooth transition from university to work environment (Gillies & Ashman, 2003; Millis & Cottell, 1998).

The notion of reformed education has emerged in statistics education in the last decade. The diffusion of this belief among statistics educators has shifted statistics education from traditional knowledge transmission to constructivist practice. The reform efforts within statistics education generally reflect university restructuring efforts that are currently progressing at various speeds throughout the United States. Over the past 10 years, a several researches have studied these issues for the introductory statistics course (Gordon & Gordon, 1992; Moore, 2000; Rao & Székely, 2000).

Previous research predicted statistical performance by examining the causal relationships between variables, such as motivation, anxiety, attitude, and achievement; however, research has been limited to analyzing such variables in isolation. For example, these studies analyzed individual assessment techniques (Chance, 1997), cooperative learning (Giraud, 1997), or online collaborative learning (Zhang & Harkness, 2002).

**Problem Statement**

The introductory statistics course is one of the most challenging required courses for students to complete for graduation. Unfortunately, many students do not regard statistics as a relevant part of their degree program, but instead view it merely as a hurdle they must overcome in order to obtain their degrees (Gal & Ginsburg, 1994; Onwuegbuzie et al., 1997). It is common to see students delay taking the statistics courses until just before graduation (Perney & Ravid, 1990).
The introductory statistics course is particularly important because, for most students, it is their only formal exposure to statistics. Their experiences in this course may affect their attitudes toward the field of statistics and thus determine whether they become consumers of statistics in the future (Onwuegbuzie et al., 1997).

However, the introductory statistics course has been viewed as difficult and unpleasant by many students and frustrating and unrewarding to teach by many instructors (Hogg, 1992). Dissatisfaction with the introductory statistics course has led statistics educators to suggest new models for the course, to lead workshops to reexamine the course, and to offer recommendations for how the course should be changed (Hogg, 1992).

A central concern has been the relationship of attitude to course performance. Previous studies have focused on the causal relationship between students’ attitudes, anxiety, prior knowledge, and statistical performance, and have found substantial impact of attitude and background on students’ statistical performance (Baloglu, 2003; Bandalos et al., 2003; Bessant, 2001; Kottke, 2000; Lalonde & Gardner, 1993; Musch & Broeder, 1999; Nasser, 2004; Schultz et al., 1998; Tremblay et al., 2000). Researchers who focused directly on the role of emotions in mathematics and statistics learning (McLeod et al., 1989) have reported that the undergraduate students in their study, who were math majors, were not very good at recognizing, managing, or overcoming their negative reactions toward statistics.

These researchers believe that even with appropriate attitudes, low levels of anxiety, and high levels of motivation, students will still have difficulties attaining course content in introductory statistics if major reforms in teaching methods are not
implemented. Despite the wide use of innovative learning and teaching strategies now observed in statistics courses, relatively little published research exists describing its holistic impact on student learning. New teaching and learning methods are often developed and implemented without the benefit of research on their effectiveness in statistics education.

Educational reform programs highlight the importance of using comprehensive approaches with a variety of interventions (Center for Mental Health in Schools, 2000; Hunt & Minstrell, 1996). Therefore, a comprehensive approach should be used to determine which aspects of a reformed statistics course predict attitude and performance where all participants will be exposed to the entire learning environment rather than just one or two new instructional strategies.

Although there have been many studies about statistical performance, few studies that have dealt with the relationships among the factors have examined mediating effects. It is important to conceptualize and empirically test a model that identifies specific activities to enhance student performance and build strong positive attitudes toward statistics. This model should aid in reforming statistics education and improve the quality of higher education.

**Background: Model for Predicting Statistics Performance in an Introductory Statistics Course**

In recent years many statisticians have become involved in the reform movement aimed at the improvement of introductory statistics. The National Science Foundation has funded numerous projects designed to implement aspects of this reform (Cobb,
1993; Moore, 1997). Moore (1997) described the reform in terms of changes in content (more data analysis, less probability), pedagogy (fewer lectures, more active learning), and technology (for data analysis and simulations). Hoaglin and Moore (1992) offered a set of readings to inform statistics instructors of new content and techniques; Garfield (1995) offered a research perspective on why and how teaching methods should be changed; and many statisticians have suggested ways to incorporate technology into the introductory course (Velleman & Moore, 1996).

The current reform movement in statistics education also emphasizes features such as statistical thinking, active learning, conceptual understanding, genuine data, use of technology, collaborative learning, and communication skills (Garfield, 1998; Garfield et al., 2002b; Gordon & Gordon, 1992). These range from a complete reform of the course, to enhancing the relevance of statistics, to emphasizing the importance of salient statistical concepts (Rumsey, 2002).

and attitudes toward statistics. Few attempts have been made to construct conceptual models involving statistics attitude and performance. Most theoretical models involving statistics attitude have been concerned with the prediction of achievement in an introductory statistics course.

What elements should be considered in order to enhance statistics performance in introductory statistics courses? It is worth the effort to develop a new model for predicting statistics performance that includes the effect of reformed introductory statistics course methods, and the causal relationship of students’ attitude variables from previous research.

A literature review of research relevant to this topic found many variables that have been studied in connection with statistics performance. The variables studied in past research on statistics performance can generally be divided into two factors: individual factors and interpersonal factors. The individual factors include students’ background, attitude, anxiety, and motivation, while interpersonal factors are defined by the nature of the group in group projects and experience with group work.

**Purpose of the Study**

This study was conducted in an effort to address some of the concerns related to statistics performance as identified from previous research. The overall goal of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance.
First, an effort was made to develop an understanding of the interrelationships of *individual* factors that students bring to an introductory statistics course. Second, an effort was made to develop an understanding of the interrelationship of *interpersonal* factors that students bring to an introductory statistics course. Third, changes in statistics performance, as a result of the degree of active engagement in the reformed course activities, were explored, especially the suggested mediating effect of individual factors and interpersonal factors and statistics performance. Finally, the goal was to extend and refine an exploratory conceptual model of statistics performance.

A preliminary model included variables that had been studied previously in connection with statistics performance. These included (a) students’ background, (b) attitude, (c) test anxiety, (d) motivation, (e) nature of the group in group projects, and (f) experience with group work. Students’ background, attitude, anxiety, and motivation variables can be categorized as individual factors, and the nature of the group in group projects and the experience with group work could be categorized as interpersonal factors.

Based on a perspective provided by ecological theory (see Figure 1-1), a preliminary model was drawn, showing the influence of both (a) students’ individual factors, as indicated by students’ background, attitude, test anxiety, and motivation and (b) students’ interpersonal factors, as indicated by the nature of the group and experiences with the group work.
Figure 1-2 shows all variables included in the preliminary model of statistics performance. These variables have been categorized and selected based on the literature review of research relevant to statistics performance. This model makes theoretical sense; however, it is important to test it empirically. A conceptual model should be testable. The identification of a model refers to the question of whether there is sufficient information (i.e., an adequate number of observed variances and covariances) to allow estimation of all of the model parameters (Kelloway, 1998; Tate, 1998). Theoretically this preliminary model is acceptable; however, in order to allow all estimates of the model parameters it is necessary to obtain a large sample size.
Figure 1-2: A preliminary model of statistics performance with all variables
Therefore, considering the realities of the preliminary model being identified, it has been modified and simplified to include one variable each for the individual domain (attitude toward statistics) and the interpersonal domain (experience with group work). These variables were chosen based on their importance to predicting statistics performance.

In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance.

In the analyses, the influence of both (a) the individual factor-attitude toward statistics and (b) the interpersonal factor-experiences with the group work was considered. Because students’ individual factor-attitude toward statistics and the interpersonal factor-experience with group work may affect statistics performance directly through mechanisms other than the degree of active engagement in the reformed course activities, the study was designed to test both the indirect effects of the individual factor-attitude toward statistics and the interpersonal factor-experience with group work through the degree of active engagement in the reformed course activities and its direct effect on statistics performance among the introductory statistics class students. The conceptual model tested is shown in Figure 1-3.
Predicted Model

Statistics Performance from an Ecological Theory Perspective

Bronfenbrenner (1979) has developed an ecological framework that identifies the interconnected systems that influence human development. Bronfenbrenner (1989) and Bronfenbrenner and Morris (1998) explained, “Ecological theory is positing that human
development is a joint function of the person and the environment where enduring interactions between a person and his/her environment, progressive complexity of these interactions, and characteristics of the developing person and the environment reciprocate to shape development” (p.227).

The cultural development from the educational system eventually depends on the way students become more capable of producing internal transformations to generate changes in the structure and functions of their mental state, as well as their aims in the learning of statistics. The ecological perspective is a belief in the necessity of viewing the individual and the environment as they relate to and define each other. The perspective of ecological theory shows the ways individual development and the social world are interrelated, and the theory links development with social context (Tudge et al., 1996). Individual development is the result of complex relationships between individuals, peer groups, and the classroom. The individual is the center of his or her social ecology. Social ecology also includes peer groups and the classroom. If the individual’s peer group supports certain behaviors in their learning process, then the individual may be more likely to engage in these behaviors. Extending outward, the classroom encompasses peer groups and the individual.

Ecological theory purports that all individuals are part of interrelated systems that locate the individual at the center and moves out from there to include all systems that affect the individual (Bronfenbrenner, 1979). Figure 1-2 above depicts the interrelatedness of these systems, which interact to influence human behavior. According to Bronfenbrenner’s theory, the individual is at the center of, and is actively involved with, this interplay of systems.
The ecological theory framework has gained increased recognition in the field of
developmental psychology (Bronfenbrenner, 1989; Capra, 2003; Nastasi, 2000; Tudge et
al., 1996; Ungar, 2002) and has been applied to investigations of many different
disciplines (Caldwell & Darling, 1999; Newes-Adeyi et al., 2000; Pugesek et al., 2003;
Ungar, 2002). This framework has not been applied in the field of statistics education but
will be valuable to help describe contextual influences on students’ statistics
performance while reflecting the interrelationships among students and contexts
(Bronfenbrenner, 1992).

In the course of students’ development, substantial consideration has been given
in the present study to contextual influences on statistics performance. Because the
ecological perspective considers and incorporates factors inherent both within a student
as well as within the student’s peers and classroom, it provides a contextual framework
to help in understanding the many different factors contributing to statistics
performance. Ecological theory is adopted in the present study as framework for a
comprehensive model of statistics performance in introductory statistics courses. This
model is shown in Figure 1-4 and hypothesizes that the individual factor and the
interpersonal factor affect statistics performance directly and indirectly through their
effects on the degree of active engagement in the reformed course activities.
Research Questions

The main purpose of this study was to determine the nature of the interrelationships among the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, the degree of active engagement in the reformed course activities, and statistics performance. In order to determine how well the conceptual model explained statistics performance, the following questions were investigated:

Figure 1-4: Conceptual framework related to factors predicting statistics performance with ecological theory perspective
• Does ecological theory explain statistics performance, and is the model that is built on this framework consistent with the data?

• Are the identified predictor variables (the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and the degree of active engagement in the reformed course activities) significant predictors of statistical performance?

• What are the direct, indirect, and total effects of the identified predictor variables on the statistical performance?

**Hypotheses**

The hypotheses tested in the present study are follows:

**Direct Effects**

**Hypothesis 1.** The individual factor-attitude toward statistics will have a direct, positive effect on statistics performance.

**Hypothesis 2.** The interpersonal factor-experience with group work will have a direct, positive effect on statistics performance.
Indirect Effects

**Hypothesis 3.** The individual factor-attitude toward statistics will have an indirect effect on statistics performance through lab quizzes. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.

**Hypothesis 4.** The individual factor-attitude toward statistics will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.

**Hypothesis 5.** The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of lab quizzes. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.
**Hypothesis 6.** The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.

**Definitions of Terms**

*The individual factor-attitude toward statistics:* Four facets of attitude toward statistics: (a) affect—positive and negative feelings concerning statistics, (b) cognitive competence—attitudes about intellectual knowledge and skills when applied to statistics, (c) value—attitudes about the usefulness, relevance, and worth of statistics; and (d) difficulty—attitudes about the difficulty of statistics as a subject (Schau et al., 1995), as measured by the Survey of Attitude toward Statistics.

*The interpersonal factor-experience with group work:* Students’ perceptions of how the group affects their learning in four areas: (a) confidence—preferences toward learning in groups inside and outside the classroom, (b) communication—group members’ communication skill to support effective group work, (c) goals—perception of clarity of goals for group work, and (d) participation—determination of degree to which participants have been active and cooperative members of the group, as measured by the Survey of Experience with Group Work.
The degree of active engagement in the reformed course activities: This refers to the students’ level of involvement in the reformed course activities. Level of involvement is a combination of participation in course activities and score of correct on statistical concept assessments. The following reformed course activities were designed to actively engage all students present.

- Lab quizzes: In-class laboratory activities engage students by hands-on experience with statistical problems in a computer lab. Statistical problems in lab quizzes were assessments of students’ progress and applications, and simulations of statistical concepts.

- Group project with peer assessment
  - Group project: Activities engage students by being completed with other students using class-generated data.
  - Peer assessment: A part of the group project activities that had been designed to involve students in assessing, critiquing, and making value judgments on the quality and standards of work of other students, and in providing feedback to peers to enable them to enhance performance.

Statistics performance: Comprehension in students’ mastery of elementary statistical concepts, as measured by the readiness assessment test scores, two mid-term exams, the final exam, and the knowledge content test scores.
• Readiness Assessment Tests (RATs): Tests that were designed to assess the understanding of the assigned reading and assignments before the class, and to provide feedback to the faculty members. RATs include two types: individual RATs and group RATs.
  o Individual RATs: Students finished assigned tests first as individuals, and turned in their answers.
  o Group RATs: After students turned in individual RATs, they retook the same test, but this time as a group of three to five.

• Two mid-term exams, the final exam, and the knowledge content test: The exams were designed to assess comprehension of statistical concepts covered in this course, as measured at different times throughout the semester.
Chapter 2

LITERATURE REVIEW

Introduction

The main purpose of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance. In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance.

Foundational support for each component of the preliminary model (see Figure 1-2) is presented in this chapter. Then, the proposed model predicting statistics performance from the perspective of ecology theory in this study is presented and defined.
Conceptualized Full Model

The introductory statistics course is one of the most challenging required courses for students to complete for graduation. Unfortunately, many students do not regard statistics to be a relevant part of their degree program, but merely a hurdle they must overcome in order to obtain their degrees (Gal & Ginsburg, 1994; Onwuegbuzie et al., 1997). Many students viewed the introductory statistics course as difficult and unpleasant (Hogg, 1992). Consequently, these students typically experience lower levels of performance on statistics exams than they do on all other examinations taken in their degree programs (Onwuegbuzie & Seaman, 1995). The introductory statistics course is particularly important because, for most students, it is their only formal exposure to statistics. Their experiences in this course may affect their attitudes toward the field of statistics, and thus determine whether they become consumers of statistics in the future (Onwuegbuzie et al., 1997).

Although there have been many studies related to understanding and predicting statistical performance, few have studied the relationship among predictors and mediating variables, such as the activities in reformed statistics courses. These studies have been concerned with the prediction of achievement in a course and employed various types of regression techniques. Therefore, development of a study model and the empirical results generated may add to the understanding of adoption and utilization processes of reformed introductory statistics course activities in higher education.
**Individual Factors**

In previous studies, many variables related to statistics performance, such as gender, previous mathematics experience, previous statistics experience, anxiety, and attitude have been investigated.

**Background-Gender**

Many researchers have explored whether gender differences are related to student attitudes or cognitive performance, with somewhat mixed results. A common assumption has been that males perform better or have higher achievement in mathematics and science courses than females. The same assumption has been made in introductory statistics as well. Numerous studies of gender differences in statistics course achievement have been conducted, resulting in different conclusions. Elmore and Vasu (1980, 1986) examined gender difference as a predictor of statistics achievement by attitudes toward the mathematics-related course work, previous mathematics coursework, spatial ability, and masculinity-femininity of interest patterns in undergraduate and graduate courses. They found that male students received significantly higher mean scores than females on statistics achievement. However, Schram (1996) used meta-analysis to synthesize the results from 13 studies and concluded that females earned higher grades and more total course points in statistics classes than males.
**Background-Major**

In a study where the same questionnaire was administered to students in different majors at different levels (first and second year) and at three different institutions, Phillips (1990) found differences in students’ attitudes toward statistics based on the discipline of study and class level. Not surprisingly, students in mathematics- or statistics-related majors had positive attitude toward statistics, but students in other majors did not. McLeod, Metzger, and Craviotto (1989) reported that undergraduate students who were not math majors were not very good at overcoming their negative reactions toward statistics. Gal and Ginsburg (1994) suggested that because of the role and relative importance of statistics for different students, “results for statistics attitudes should be reported for students at different stages of academic careers and for those majoring in different fields.”

**Background-Math Experience**

Not only the number of previous mathematics courses but also mathematical training can influence the performance of the introductory statistics student (Tomazic & Katz, 1988). Students who have not taken a mathematics course recently do not perform as well in applied statistics as those who have taken mathematics more recently (Bandalos et al., 1995; Huberty et al., 1993). Harvey, Plake, and Wise (1985) found the number of math courses taken in high school and in college to be significantly and positively correlated with a first examination in a statistics course. Additionally, there is
a positive relationship between the number of prior mathematics courses completed and students’ achievement in statistics (Elmore et al., 1993; Fenster, 1992b).

**Background-Statistics Experience**

Prior experience and achievement are likely to influence student learning, especially when students are learning new but related tasks. Theories of cognition related to information processing suggest that previously learned relevant information that can be retrieved from long term memory facilitates the processing of new information (Woolfolk, 1995). Studies by Elmore and Vasu (1980, 1986) found that prior courses in statistics significantly predicted statistics achievement over and above other variables such as spatial ability and feminist attitude. Brown and Brown (1995) examined the influence of grades in the prerequisite course on the attitudes of students in a business statistics course. Theory would suggest that the more successful the prior experience and achievement, the more likely it is to positively affect student efficacy and attitude. Prior experience and achievement are likely to influence the individual learner in statistics courses.

**Motivation**

Brophy (1988) described motivation to learn as a student’s tendency to find academic activities meaningful and worthwhile when deriving the intended benefits of those activities in education contexts. Researchers have often found a strong correlation between motivation to learn and student achievement (Wang et al., 1993; Weinstein,
Curda (1997) explored learner characteristics related to motivation and their influences on achievement in statistics. Results found that deep processing strategy use, self-efficacy, and learning goals have direct effects on statistics achievement, and self-efficacy played the biggest role in accounting for variance in many key variables related to achievement. Another study conducted by Schultz, Drogosz, and White (1998) investigated motivational variables and elaboration learning strategies as factors that lead to success in statistics. The results of this study showed that motivation variables influenced performance in the introduction to statistics class. Lalonde and Gardner (1993) investigated the combined effect of motivation and attitudes on achievement in statistics through effort and found this effect to be positive and significant.

Motivation appears as a predictive construct affecting the commitment to face the study of introductory statistics (Gal & Ginsburg, 1994; Johnson, 1988). Students’ feelings about statistics education, and the effects of these feelings on resulting learning, knowledge, and further interest in statistics, deserve more attention from statistics educators.

**Anxiety**

Anxiety is generally defined as feelings of insecurity (Rost & Schermer, 1989), feelings of mingled dread and apprehension (Chaplin, 1985), or an unpleasant emotional state or condition (Spielberger, 1983). Researchers relating anxiety and learning (Green, 1994) have found that some anxiety in a learning situation can enhance student learning,
but too much can be detrimental. Mixed results have been reported relating measures of attitude and anxiety to measures of statistics achievement.

Feinberg and Halperin (1978) and Zeidner (1991) recognized that statistics anxiety may serve as a detriment to performance in statistics and, consequently, have a negative impact on a variety of academic situations. Most of the previous research has examined statistics anxiety indirectly by means of instruments designed to assess statistics test anxiety (Benson, 1989; Benson & Bandalos, 1989), attitudes toward statistics (Fenster, 1992a; Gal & Ginsburg, 1994; Schau et al., 1995), or mathematics anxiety (Pretorius & Norman, 1992). Birenbaum and Eylath (1994) found a correlation of -.11 between statistics anxiety as measured by a single self-report item at the beginning of an educational research course and students’ grades on the final exam.

It is generally accepted that a higher level of anxiety results in a lower level of performance because test anxiety interrupts the recall of previously learned information, thereby lowering test and, ultimately, course performance (Hembree, 1988). More recently, Onwuegbuzie (1998, 2000) reported findings indicating that low achievement of college students was related to higher levels of statistics anxiety and low computation self-concept. Although statistics anxiety has been clearly identified as a persistent difficulty for many university students, very little research is evident in which this issue is explicitly addressed.
Attitude

Attitudes are defined as evident in behaviors such as approaching or avoiding certain situations or learning tasks. In particular, students’ attitudes toward statistics that change or are developed during a statistics course may affect the extent to which students pursue advanced coursework in statistics, or the extent to which they implement the concepts they have learned (Gal et al., 1997). Additionally, attitude toward statistics has primarily focused on its relationship to achievement. Many of the studies involving attitude toward statistics have used these affective variables as predictors of performance in a statistics course. Results have varied depending on the type of achievement measures, the attitude measure, the time of administration of the attitude instrument and/or the achievement measures, and the statistical procedures used to examine the relationship.

Cashin and Elmore (2005) confirmed the importance of students’ pre- and post-course attitudes toward statistics in predicting their achievement in introductory inferential statistics courses.

The association of statistics attitude and achievement has been explored for various levels of students, majors, and types of statistics courses. Studies by Ellman (1991) reported a correlation of .06 and .09, respectively, between the final exam score and results from the pre- and posttests from a semantic differential scale for mathematics attitude administered to students in a graduate level educational statistics course.

Nist, Olejnik, and Allen (1994) reported positive correlations between the survey of attitude toward statistics administered at the beginning of a course and three exams
taken at different times during a graduate introductory education statistics methods class.

The relationship between statistics attitude and statistics performance has been a primary concern for researchers in statistics education. Recent studies investigating the effects of students' attitude have confirmed the importance of these variables when considering student academic performance (Fenster, 1992b; Waters et al., 1988). A definite pattern of higher correlations is observed when end-of-course attitude measurements are related to course performance. However, most studies have shown a low to moderate association between statistics attitude and achievement (Kottke, 2000; Scott, 2002; Townsend et al., 1998a).

Birenbaum and Eylath (1994) reported a high correlation between statistics attitude and students' willingness to enroll in an elective statistics course.

Gal and Ginsburg (1993) argued that the lack of a clear definition of attitude toward statistics makes it difficult to establish construct validity and can contribute to confusing and contradictory results. In addition, Gal and Ginsburg (1994) reported that “the body of research on students' attitude, beliefs, and affect related directly to statistics education is very small and problematic.” The authors of the Survey of Attitudes Toward Statistics (SATS) have chronicled a rigorous development and validation process (Cashin & Elmore, 2005; Dauphinee et al., 1997; Hilton et al., 2004; Schau et al., 1995; Susan & Patricia, 2005). The SATS seemed to provide some improvement over previously reported instruments measuring statistics attitude.

A number of studies have investigated the relationship between attitudes toward statistics and performance in introductory courses using a variety of correlational and
regression techniques. Results indicated a small to moderate positive relationship. This relationship appears to be fairly consistent regardless of the instrument used, the time of administration of either the attitude or performance measure, or the level of the students (Wisenbaker et al., 2000).

**Modeling Statistics Performance**

There are numerous studies that have examined the predictors of success in statistics performance. Many suggested predictors are characteristics that learners bring with them when enrolling in a statistics course. Other predictors include approaches to learning and strategies students use to learn statistics during enrollment in the course.

Lalonde and Gardner (1993) argued that learning statistics is akin to learning a foreign language, and Onwuegbuzie (2003) also adopted an anxiety-expectation model of foreign language achievement as a basis for modeling statistics achievement. Lalonde and Gardner (1993) adapted a model from Gardner’s second language learning model for the framework for understanding and predicting statistics performance. A causal model linking mathematical aptitude, math anxiety, and attitudinal and motivational variables was proposed and tested using a LISREL causal modeling procedure. Their model indicated that mathematics background did not affect attitudes directly, but indirectly through anxiety.

Tremblay, Gardner, and Heipel (2000) tested the model that individual difference variables in motivation, anxiety, attitudes, and aptitude related to each other and to achievement in a statistics course. Results showed that both motivation and aptitude
contribute to achievement in statistics, as was also suggested by Lalonde and Gardner (1993).

Del Vecchio (1994) used the Tinto model for college attrition as a conceptual guide to study an introductory undergraduate statistics course. Hierarchical logistic regression was used to investigate the role that certain demographic and background variables as well as mathematics self-concept and statistics attitude played in student persistence in an introductory statistics courses. Prior grade point average and the survey of attitude toward statistics (SATS), cognitive competence, and difficulty scales were the only variables that contributed to the model for both males and females. For female students, math self-concept and the number of college math and statistics courses also contributed to the classification model for identifying students who could be expected to complete the introductory statistics course.

Scott (2002) examined the role of attitudes toward statistics, mathematics anxiety, mathematics attitude, mathematics background, demographic variables, and performance for students in an undergraduate introductory statistics course. Path analysis was used to develop a conceptual model for statistics attitude and performance in the course using mathematics attitude, mathematics anxiety, and prerequisite grade as the exogenous variables. In the path model, performance in the course was not influenced by either the pretest or posttest SATS. Performance during the statistics course did affect the posttest SATS scores.

Bandalos, Finney, and Geske (2003) adopted a model from goal theory as a framework for a comprehensive model of achievement in an introductory statistics course, and tested it using structural equation modeling techniques. The results showed
that the achievement goals predicted self-reported strategy use, self-efficacy, and test anxiety.

Table 2-1 presents a summary of previous research conducted to predict statistics performance. These studies suggested several individual variables that play potentially important roles in statistics performance in the introductory statistics class.
Table 2-1: A Summary of Previous Research

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<tr>
<th>Study</th>
<th>Variables</th>
<th>Methods</th>
<th>Results</th>
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<tbody>
<tr>
<td>Lalonde &amp; Gardner</td>
<td>Mathematical attitude</td>
<td>Causal modeling analysis</td>
<td>The results indicated that mathematics background does not affect attitudes directly, but indirectly through anxiety.</td>
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<tr>
<td>(1993)</td>
<td>Mathematical achievement</td>
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<td>Mathematical history</td>
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<td></td>
<td>Situational anxiety</td>
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<td>• Statistics anxiety</td>
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<td>• Number anxiety</td>
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<td></td>
<td>Attitude-motivation index (+)</td>
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<td></td>
<td>• Attitude toward statistics</td>
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<td>• Statistical course evaluation</td>
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<td></td>
<td>• Attitude toward learning statistics</td>
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<td></td>
<td>• Motivation</td>
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<td></td>
<td>Effort: Assignments</td>
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<td></td>
<td>Achievement</td>
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<tr>
<td>Del Vecchio</td>
<td>Gender</td>
<td>Hierarchical logistic</td>
<td>Prior grade point average and the survey of attitudes toward statistics and difficulty scales were the only variables that contributed to the model for both males and females. For female students, math self-concept and the number of college math and statistics courses also contributed to the classification model for identifying students who could be expected to complete the introductory statistics course.</td>
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<tr>
<td>(1994)</td>
<td>Math self-concept (+)</td>
<td>regression analysis</td>
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<td></td>
<td>Number of college math and statistics course (+)</td>
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<td></td>
<td>Prior grade point average (+)</td>
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<tr>
<td></td>
<td>Statistics attitude (+)</td>
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<td></td>
<td>Persistence in statistics course</td>
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Table 2-1: continued

<table>
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<tr>
<th>Study</th>
<th>Variables</th>
<th>Methods</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schultz et al. (1998)</td>
<td>Background variables (Pre-statistics, Pre-math, Test anxiety) Attitude variables (Affect for statistics, Value of statistics) Motivational variables (Confidence, Control of learning beliefs) Learning strategies variables (Elaboration) Course grade</td>
<td>Hierarchical regression analysis</td>
<td>Background variables and attitude variables made contributions to the variance. The results indicated that motivation influenced performance; however, learning strategies variables did not account for unique variance in regression, but in the cluster analysis, their use tended to be related to performance. The full model with all variables included accounted for 47% of the variance in course grade.</td>
</tr>
<tr>
<td>Tremblay et al. (2000)</td>
<td>Mathematics course average Psychology course average Motivational intensity (+) Desire to learn statistics (+) Interest in psychology Interest in mathematics Numerical anxiety Statistical anxiety Attitude toward learning statistics (+) Attitude toward the course Attitude toward the professor Final statistics exam</td>
<td>SEM</td>
<td>Results support the hypotheses that both motivation and attitude contribute to the prediction of achievement in statistics as suggested by R. N. Lalonde and R. C. Gardner (1993). Furthermore, support for a direct link between anxiety and achievement in statistics was found.</td>
</tr>
<tr>
<td>Scott (2002)</td>
<td>Attitudes toward statistics (SATS) Mathematics anxiety Mathematics attitude Mathematics background Demographic variables Performance</td>
<td>Path Analysis</td>
<td>In the path model, performance in the course was not influenced by either the pretest or posttest SATS. Performance during the statistics course did affect the posttest SATS scores.</td>
</tr>
</tbody>
</table>
Summary of Research on Individual Factors

The individual factors included in the preliminary model in the present study were gender, major, math experience, statistics experience, motivation, anxiety and attitude (see Figure 1-2). These variables were selected from various studies on statistics performance. This model makes theoretical sense; however, it is important to test it empirically. In order to develop a testable model, the attitude toward statistics variable was selected as the most important individual factor by the researcher.

Student attitudes toward statistics are important because they may influence the learning process. The attitudes and beliefs about statistics which students bring to the classroom have the potential to positively or negatively impact their ability to learn and apply statistical concepts. Negative attitudes can be disadvantageous to the learning of statistics, whereas positive attitudes can be beneficial for effective learning (Baloglu, 2003; Gal & Ginsburg, 1994; Onwuegbuze, 1995; Waters et al., 1988; Wise, 1985).

Only a few researchers have attempted interventions to improve attitudes for students in introductory statistics courses. Most attempts to improve attitudes of introductory statistics students have involved some alteration of classroom instruction. It is important to test the construct validity of the attitude toward statistics and the intervention effects to improve attitudes for students in introductory statistics courses.

A measurement model of the attitude toward statistics included four different factors (affect, cognitive competence, value, and difficulty), and is presented in Figure 2-1.
Interpersonal Factors

Collaborative learning or group work has received a lot of attention in higher education in recent years and has established itself as a widespread form of student-centered learning.

Collaborative learning is the instructional use of small groups in which students work together to maximize their own learning, as well as that of their group members (Johnson et al., 1991). It has been reported that the group learning approach has been applied to a large variety of disciplines and there are number of methods by which such work can be assessed (Lejk & Wyvill, 2001). Collaborative learning, cooperative learning, group work, and group projects are terms used almost interchangeably. However, group learning is only a means to help students learn more effectively and it does not
lead to assessment of students in groups by default (Li, 2001). As the collaborative learning approaches in higher education increase, so do the challenges of evaluating these approaches and deriving from them principles of good practice (Barron, 2000; Michalchik et al., 2001).

Collaborative learning, extensively used and researched in elementary and secondary schools (Slavin, 1990), emerged as an important pedagogy in higher education during the late 1980s (Bruffee, 1999; Goodsell, 1992). Collaborative learning restructures the classroom away from the traditional lecture to small-group work requiring intensive interaction between students and the faculty member while working through complex projects.

There is a growing consensus among statistics educators that the introductory statistics course needs to be reformed (see, for example, Cobb, 1993b, and Snee, 1993). One of the arguments for reform is that students learn better and retain more if they engage in learning activities that require them to think and process information rather than passively listen to lectures. Hogg (1991) suggested that using cooperative learning techniques would promote active learning. Garfield (1993) summarized relevant literature on cooperative learning and gave guidelines for getting started and examples of its use. Others have been developing active learning materials for use in statistics courses (Perry & Kader, 1992; Snell & Finn, 1992).

With more emphasis on active learning, there is naturally an increased emphasis on group work. Many classroom activities are carried out in teams of students, either by design or by necessity due to limited resources or materials. The need for students to be working in groups at their future workplace is often discussed as one motivator for
emphasizing team projects in an introductory statistics course as well (Brandsma, 2000; Chance, 1996; Jones, 1991). Group learning is intended to introduce students to real-world experiences before graduation along with all of the theoretical advantages. More and more college and university faculty are assigning students to work in groups to solve real-world or simulated problems (Gamson, 1994).

Ideal learning or classroom groups are described by Johnson and Johnson (1992) as having the following characteristics: (1) a clearly defined goal, (2) cooperative or collaborative structure, (3) shared responsibilities, and (4) communication among members, and between members and an instructor.

Group members who have goals and objectives related to the group are more effective than members who do not. Although the instructor develops an objective for the group, the group itself should still develop its own “team goals.” The team goals should be agreed upon by all members of the group, and each individual member must contribute his or her own success to the success of the group in order to maximize the learning potential of the entire group (Cooper, Robinson, & McKinney, 1994).

Effective group members either have or learn facilitative communication skills, which means that they seek to reduce personal barriers to accurate listening so that they not only hear content from the speaker, they understand the deeper meaning. The importance of communication skills for group work cannot be overestimated. Developing positive relationships is the single most important step in conducting and participating in a productive group. Communication skills are also crucial in developing the group and fostering its growth and task accomplishment (Carroll et al., 1997; Corey & Corey, 1998).
Inclusion is an important concept for groups. If the group is to be effective and productive, each member must make a contribution. While it is possible to get the project accomplished when not all members contribute, such a situation is a failure of the group. Studies continue to show the superiority of group productivity over individual productivity for many tasks (Johnson & Johnson, 1992).

**Effectiveness of Collaborative Learning**

Researchers studying the use of cooperative learning at the college level have found positive results. In one study, the use of learning partners and peer monitors resulted in improved performance in problem solving, on quizzes, and on tests (Dees, 1991). In another study, students learned just as well in cooperative as in traditional settings and developed more positive attitudes toward mathematics (Davidson & Kroll, 1991). Webb (1982, 1983) gathered and analyzed data on student interactions that demonstrate that problem solving and concept learning may be enhanced by the use of cooperative groups. Students in cooperative structures performed better than their peers in traditional classrooms on questions involving higher level thinking (Sharan, 1980).

Cooperative learning has been linked to other positive social or affective outcomes. One benefit is the increase in social skills of students who participate in group work (Slavin, 1990). By working together, students learn to be tactful, to manage conflicts effectively, and to respect the opinions of others (Augustine et al., 1989-90). Learning social skills may be particularly important in adolescence, a period when the need to belong conflicts with the need to be recognized as an individual (Wood, 1987).
Group work addresses this conflict provided the groups are small enough for individual recognition. Cooperative learning has also been linked to increases in self-esteem, attendance, time on task, enjoyment of school and classes, and motivation to learn, as well as a decrease in dependence on the teacher (Augustine et al., 1989-90; Good et al., 1989-90; Slavin, 1990; Wood, 1987). Perhaps one of the most important benefits of cooperative learning has been more positive intergroup relations. Improved race relations, as well as increased acceptance of mainstreamed children, have frequently been reported.

These positive social, affective, and behavioral benefits of cooperative learning have also been specifically linked to cooperative learning in mathematics classrooms (Davidson, 1985; Mulryan, 1994, 1995; Slavin, 1985). The introduction of group work and activities during lectures can produce dramatic improvements in the reception of the course, especially among college students with limited mathematical background (Conners et al., 1998; Courtney et al., 1994; Potthast, 1999; Townsend et al., 1998b).

Courtney et al. (1994) compared the effect of cooperative learning versus a traditional lecture on graduate students in education who were taking a general statistics course. They found a large reduction in anxiety and improved feeling of efficacy among the students in the cooperative learning section.

Keeler and Steinhorst (1995) compared undergraduate students who took a traditional lecture course versus those who participated in a cooperative learning course. The authors found that students performed better and showed more satisfaction with the course in the cooperative learning structure.
Giraud (1997) described similar results. Students taking a cooperative learning version of an introductory statistics course improved their performance and indicated greater satisfaction with the course. Adding to these results, Townsend et al. (1998a) found that a cooperative learning approach increased students’ mathematical self-concept and decreased math anxiety, although these effects were mediated by students’ previous math training.

Potthast (1999) found that students presented with the same topics in a cooperative learning experience improved their performance on course tests, their attitudes with respect to statistics, and their confidence in their competence. Also, Magel (1996) found that the effect of group work during lectures helped to increase performance on the course exams. These results replicate in consistent manner the effect of in-class group work on hands-on activities.

Studies have shown the positive effect of cooperative learning on students’ achievement. As Hertz-Lazarovits and Miller (1992) noted, collaborative learning should be used not just “as a means of reaching end goals such as enhancing academic achievement and increasing positive interpersonal and intergroup relations,” but also “as an end product that is valuable in and of itself” (p.253). That is, providing students with group work opportunities is essential if they are to develop an appreciation for the benefits of collaboration.

Researchers were quite confident that the composition of the groups would have a significant impact on their success or failure in the learning process (Feichtner, 1985). Teachers have identified essential characteristics in the formation of the group. Luft (1990) suggested that these groups have to be heterogeneous in ability, motivation,
gender, age, and race. Cooperative learning has a positive effect on students’ helping interactions and learning research also shows that students of different ability level differentially benefit from learning in groups (Peterson & Miller, 2004).

**Experience with Group Work**

Group work is influenced by whether or not group members reflect on how well they worked together. Group processing may be defined as reflecting on the group’s work and identifying what was helpful and what was not and possible modifications that can be made. The main purpose is to improve the effectiveness of the members in contributing to collaborative efforts to achieve the group’s goal (Bowe, 2001; Johnson, Johnson, & Smith, 1991).

Whicker et al. (1997) surveyed student attitudes toward groups. The study results showed that students liked receiving help from each other. Other comments from students were that (1) it was easier to work on complex or difficult problems together, (2) they liked the opportunity for discussion and sharing ideas, (3) they learned more in cooperative groups, and (4) they needed suggestions and advice on how to work out problems.

Peterson and Miller (2004) studied the quality of student experience during cooperative learning within a large group instruction setting. They found that the overall quality of experience was greater for thinking on task, student engagement, and perception of task importance, and that optimal level of change and skill were achieved. Results suggest that cooperative learning with undergraduate students can lead to
greater cognitive involvement; somewhat greater activation; and higher levels of motivation, including higher engagement, greater perceived importance of the tasks, and more optimal levels of challenge in relation to skill (Peterson & Miller, 2004).

Research conducted by Springer, Stanne, and Donovan (1999) indicated that participation in group projects promotes students’ academic achievement, persistence in college, and positive attitudes about learning.

However, Colbeck, Campbell, and Bjorklund (2000) found that many students had negative reactions to group learning experiences. However, this study also revealed that many students, nevertheless, perceived that some of their group experiences were positive.

Feichtner and Davis (1984-85) revealed that, based on a survey of student learning groups, many students are leaving the classroom experiencing only the frustrations of group work and not the numerous benefits possible through team effects.

Past research has shown that group work experience has a significant effect on individual or group performance. However, understanding how students experience various instructional activities is important because their experiences will influence not only what they learn in their academic subjects but also what they learn about the value of collaboration. However, while support for group work is unequivocal, few studies have attempted to identify the variables that mediate the relationship between group experiences and learning outcomes (Gillies & Ashman, 1998). Identifying these variables is crucial to understanding not only which ones mediate the teaching-learning process but also how they influence this process. In essence, what is it that happens in groups that affects group behaviors, interactions, and learning?
**Summary of Research on Interpersonal Factors**

The interpersonal factors included in the preliminary model were nature of group and experience with group work (see Figure 1-2). These variables were selected from various studies on statistics performance. This model makes theoretical sense; however, it important to test it empirically. In order to develop a testable model, the experience with group work variable was selected as the most important interpersonal factor by the researcher.

Collaborative learning or group work has been used in higher education in recent years, and most researchers have reported that collaborative learning as an instructional strategy improved students’ performance. Research suggests that collaborative learning can have a positive relationship on students’ motivation level and learning outcomes. Despite the importance and positive effects of collaborative learning, relatively little published research exists describing perceptions of experience with group work. However, previous research has not focused on students’ perceptions about experience with group work, and how the perceptions affect students’ performance. Therefore, the relationships between students’ perceptions of experience with group work and their learning need to be further examined.

A measurement model of the experience with group work includes four different factors (confidence in group, communication, goals, and participation), and is presented in Figure 2-2.
Reformed Introductory Statistics Course Activities

Statistics has gained recognition as an important component of the precollege mathematics and science curriculum. Establishing a place in the elementary and secondary curriculum led to the production of new instructional materials for elementary and secondary schools (Gal & Garfield, 1997; Gal et al., 1992). At the college level, where statistics courses have traditionally been taught, changes in content and methods to focus on statistical thinking are being recommended as part of a “statistics reform” effort (Butler, 1998; Cobb, 1992, 2000; Garfield et al., 2002).

In 1992, the American Statistical Association (ASA) and the Mathematical Association of America (MAA) formed a joint committee to study the teaching of introductory statistics. Their three main recommendations were to (a) emphasize

![Figure 2-2: A measurement model for the experience with group work](image)
statistical thinking, including the need for data and the importance of data collection, (b) use more data and concepts with less theory and fewer recipes, and (c) foster active learning, including group problem solving and discussion, lab exercises, demonstrations based on class-generated data, written and oral presentations, and projects, either group or individual (Cobb, 1992).

More recently, a movement to reform the teaching of statistics has called for researchers and teachers to focus on the synergy between content, pedagogy, and technology (Moore, 1992; Moore, 1997). Not only should students be active participants assigned structured activities that focus on statistical concepts and ideas that are nonmathematical in nature, but content and methods should be strongly influenced by technology. The computer and other uses of technology in the statistics classroom as well as new and innovative teaching strategies continue to offer teachers (and students) many alternatives.

**Readiness Assessment Tests**

Statistics education experts have stressed that instructors who want students to think in statistical ways have to lecture less and find ways to engage students actively (Cobb, 2000; delMas et al., 1999; Moore, 2000). These recommendations have been incorporated into recent curricular reform projects.

The readiness assessment tests (RATs) are a method to make sure students are ready to learn, and to assess their readiness by testing them on reading materials before the unit, instead of at the end of a unit. The purpose of the RATs was to provide
valuable formative feedback to both the students and the faculty member. Analysis of student answers helped faculty target their lectures and course assignments to clarify misconceptions and give additional practice.

The readiness assessment test process allowed instructors to virtually eliminate class time that was often wasted covering material that students could learn on their own. Time was saved because the instructor’s input occurred after students had: (1) individually studied the material, (2) taken an individual test focused on key concepts from the reading assignment, (3) retaken the same test as a member of a learning group, and (4) completed a focused re-study of the most difficult concepts (Michaelsen, 2002a).

As a result, the instructor was aware of any specific concepts that needed additional attention so that he or she could correct students’ misunderstandings and still have ample time to allow students to tackle the application-oriented assignments to develop students’ higher-level learning skills (Stanley & Porter, 2002). As an integral part of the group readiness assessment test process, the discussion required the group to choose a group answer, which served as an excellent review of the readings and provided the opportunity for peer teaching (Michaelsen, 2002b).

**Practice with Content and Technology through Lab Quizzes**

Inspired by the evaluation of a calculus reform course, a study was conducted by Garfield (2000) to evaluate how the reform movement in statistics education affected the teaching of introductory statistics courses and how distinctly statistics is taught in different departments and institutions. A large percentage of respondents described
changes made in the past few years, with the most frequent changes being in the use of
technology, followed by teaching methods and course content. Reform efforts and the
increased availability of technology resources appeared to be affecting many
introductory statistics courses. In response to this challenge, researchers have been
developing curricular materials for statistical concepts, methods, and theory through a
data-oriented, active learning pedagogical approach.

Analyzing data surrounding real problems promotes the relevance of statistics. As
students perceive the importance of statistics, their motivation for studying statistics
should increase (Boger, 2001). Smith (1998) documented the impact of student-generated
data on exam scores. After restructuring an introductory statistics course to include a
semester-long sequence of projects in which the students collected their own data, Smith
observed that students’ test scores improved dramatically.

Cobb (1993) cited the advantages of hands-on activities in which students are
actively involved in data production. Because the data are fresh, not someone’s leftovers,
students are nearly always motivated to analyze the data. In fact, Fillebrown (1994)
found similar interest and motivation among her students when they collected their own
data.

**Group Projects with Peer Assessment**

Students learn by active involvement with the material, and they learn to do well
only what they practice (Garfield, 1992; Garfield, 1995). Many statistics courses are
shifting focus (Cobb, 1993), emphasizing skills such as the ability to interpret, evaluate,
and apply statistical ideas over procedural calculations. Many of these outcomes are not adequately assessed using traditional tests, which too often emphasize the final numerical answer over the reasoning process (Garfield, 1997; Garfield et al., 2002). Thus, instructors need to accompany these new instructional aims with more authentic assessment techniques that address students’ ability to evaluate and utilize statistical knowledge in new domains, communicate and justify statistical results, and produce and interpret computer output. Further, students need to receive feedback not only on their exam performance, but also constructive indications of their strengths and weaknesses, guidelines for improving their understanding, and challenges to extend their knowledge.

Perhaps one solution is to use an approach that encourages student involvement in the learning process and incorporates non-traditional assessment techniques such as peer assessment (Pond et al., 1995). Peer assessment is an interactive and dynamic process that involves learners in assessing, critiquing and making value judgments on the quality and standard of work of other learners, and providing feedback to peers to enable them to enhance performance (Falchikov & Goldfinch, 2000; Juwah, 2003; Topping, 1998). Instruction becomes more meaningful when teaching and assessment activities are integrated rather than conducted as separate classroom routines (Calfree & Heibert, 1989). Peer assessment is one type of collaborative classroom activity that provides valuable learning experiences by engaging students in the process of evaluating assignments or projects completed by their classmates (Bangert, 2001).

Based on these previous findings and recommendations, in the present study three learning activities were designed into the reformed introductory statistics courses:
(a) readiness assessment tests, (b) lab quizzes incorporating technology, and (c) collaborative learning with peer assessment. These three learning activities were thought to be important in technology-enhanced practice exercises, and active and collaborative learning.

**The Proposed Target Model of Predicting Statistics Performance**

A literature review of research relevant to this topic found many variables that have been studied in connection with statistics performance (see Figure 1-2). While this model makes theoretical sense, testing it empirically is also important. Therefore, the preliminary model must be reduced to a testable model from the perspective of ecology theory. Based on previous research, three major factors that affect statistics performance are: 1) individual factor-attitude toward statistics, 2) interpersonal factor-experience with group work, and 3) the reformed introductory statistics course activities that have been identified for this study. The proposed structural path model to be tested in this study is shown in Figure 1-3. Figure 1-4 describes a conceptual framework of statistical performance from a perspective of ecological theory. There are three measurement models included in the proposed model of predicting statistics performance: (a) individual factor-attitude toward statistics, (b) interpersonal factor-experiences with the group work, and (c) statistics performance in the reformed introductory courses. The study was designed to test both the indirect effects of the individual factor-attitude toward statistics and the interpersonal factor-experience with group work through the
performance in the reformed introductory statistics course and these factors’ direct effect on statistics performance in the reformed introductory courses.
Chapter 3

METHODS

Introduction

The main purpose of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance. In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance. The approval for the use of human participants’ secondary data was obtained from the Pennsylvania State University Office for Research Protections, Institutional Review Board Committee (see Appendix A). This study uses existing data collected during Fall 2004 by the Pennsylvania State University’s Center for Teaching Excellence on a statistics course that the center and the course faculty redesigned according to innovative ways of teaching.
Fall 2004 Refined Statistics Course Description

An existing statistics course\(^1\) was reformed by the University’s Center for Teaching Excellence group during 1999-2000 and implemented in Fall 2004. In the traditional course, students attended three lectures and two recitation sections each week. In the reformed course, students spent one session a week in a large lecture and two sessions in a computer lab, actively working through statistical problems under the guidance of experienced instructors. The faculty members in the course each taught the lecture session and a faculty member and a graduate teaching assistant co-taught the computer lab sessions. The large lecture session provided an overview of the week’s topics. The time in the labs was divided between assessments of student progress and applications and simulations of statistical concepts.

The goals for the redesign were to increase students’ ability to understand and apply basic concepts of statistics, actively participate in data analysis and design, critically evaluate reports containing statistical analyses of surveys and experiments, and actively engage with course materials and other students, as well as to provide more opportunity for one-to-one interaction with faculty (Lane & Aleksic, 2003). The reformed course capitalized on technology-enhanced practice exercises and active and

\(^1\) From Spring 1999 to Fall 2000, a team of Penn State statistics faculty, in collaboration with Penn State’s Schreyer Institute for Teaching Excellence and the Center for Academic Computing, redesigned the elementary statistics course to emphasize statistical literacy over formulas and improve the retention and transfer of statistical concepts (Roberts, 2000). Dr. William Harkness led the team and the redesign efforts and has concentrated on pedagogy and instructional design in statistics education with support from the National Science Foundation and Pew Charitable Trusts Foundation. The project mainly focused on selecting and sequencing of course materials, creating the course Web site and interactive course assignments, piloting the changes in the course, and collecting baseline data and preliminary assessment information for the new design.
collaborative learning as a means of giving students the opportunity to apply statistical
concepts (Chrisman & Harvey, 1998).

The course Web site offered many new advances. In the computer labs, students
were divided into collaborative learning groups to enable more student-to-student
interaction. In these labs, students were either assessed on their understanding of the
pre-readings and assignments or they spent class time applying statistical concepts to
real-world problems.

The innovative class activities for the reformed introductory class course
included:

**Readiness Assessment Tests (individual and group)**

The first in-class activity in each instructional unit was the readiness assessment
test (RAT) over the set of assigned readings. When students finished the individual RAT,
they turned in their answers and immediately proceeded to the group activity of the
RAT process. During this phase, students retook the same test, but this time as a group.
To complete the group test, members needed to reach agreement on each test question.
As an integral part of the group readiness assessment test process, the discussion
required the group to choose a group answer, which served as an excellent review of the
readings and provided the opportunity for peer teaching (Michaelsen, 2002b).

RATs were a method to make sure students were ready to learn and to assess
their readiness by testing them on reading materials before the unit, instead of at the end
of a unit. The purpose of the RATs was to provide valuable formative feedback to both
the students and the faculty members. Analysis of student answers helped faculty target
their lectures and course assignments to clarify misconceptions and give additional practice.

The readiness assessment test process allowed instructors to virtually eliminate class time that was often wasted covering material that students could learn on their own. Time was saved because the instructor’s input occurred after students had: (1) individually studied the material, (2) taken an individual test focused on key concepts from the reading assignment, (3) retaken the same test as a member of a learning group, and (4) completed a focused re-study of the most difficult concepts (Michaelsen, 2002a). As a result, the instructor was aware of any specific concepts that needed additional attention so that he or she could correct students’ misunderstandings and still have ample time to allow students to tackle the application-oriented assignments to develop students’ higher-level learning skills (Stanley & Porter, 2002).

Laboratory Quizzes

The laboratory classroom was equipped with laptop computers that were Internet-connected and had MINITAB (statistical software) installed. Complete instructions were given for the use of MINITAB in the laboratory session. Each session included a short answer and an extended writing assignment. The short answer writing assignment could be completed reasonably quickly. The extended writing assignments were designed to produce formal reports.

The purpose of the laboratory quiz activities was to provide students’ hands-on experiences with statistical problems in a computer lab, and an opportunity to apply statistical concepts to real-world problems.
The instructor handed out a set of questions for groups of four to five students to answer. While the students were working on the questions, a graduate assistant and the instructor walked around the room answering questions and giving immediate feedback about the group answers. The instructor collected and graded these activities.

**Group Problem Solving with Peer Assessment**

The group problem solving with peer assessment activities had been designed to be completed with other students using class-generated data with peer assessment. Students formed three- to five-member groups at the beginning of the semester and worked with this same group throughout the semester.

Statistical concepts are best learned in the context of real data sets (Cobb, 1992). In the reformed introductory statistics course, students took an online background survey using the ANGEL survey tool (see Appendix B). These survey results were used in the group problem solving activity as class-generated data, so that students would become actively engaged in their learning process.

The instructor identified peer assessment criteria, and provided a structure for group problem solving activities (see Appendix C) and peer assessment (see Appendix D). Groups worked actively together to prepare the final report. Individual students were randomly assigned a final report from another group and asked to provide a peer review according to the specified rubric. Once each student submitted a peer assessment, each group received a summary of the peer assessment feedback. Based on the peer assessment feedback, each group worked again and resubmitted the final report to the instructor, reflecting the students’ own learning and performance.
Participants

The data were obtained from a 2004 fall semester introductory statistics course with 299 students. Therefore, the original cases included a total of 299 students in the full data set. Twelve students added the course, and 38 had incomplete data, due to missing items, or missing surveys (see Table 3-1).

In this study, listwise deletion was used to screen for the missing data, which means that 50 incomplete data points were eliminated from further analysis. A total of 249 students’ data, or 83 percent of the entire data set, were used in the analysis. In this final data set, there were no missing items or cases after listwise deletion. Therefore no treatment for missing data was needed.

The missing data in this study may have had a pattern. The researcher could not detect reasons for dropping the course. It appeared that subjects who had missing data were high achieving students because more than 50 percent received a course grade of B or higher (See Table 3-1). One reason may be that students may have concentrated on preparing for the final exam. Therefore, the results may not generalize to those for whom the scores are missing.
Table 3-1: Grade Distribution those in the Final Study Sample vs. Those with Missing Data

<table>
<thead>
<tr>
<th>Grade</th>
<th>N</th>
<th>Study Sample</th>
<th>Add</th>
<th>Missing Survey</th>
<th>Missing Case</th>
<th>Sub-Total</th>
<th>Total</th>
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<td>97</td>
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<td>3</td>
<td></td>
<td></td>
<td>8</td>
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<td>% within Grade</td>
<td>92.4%</td>
<td>2.9%</td>
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<td>7.6%</td>
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<td>% of Total</td>
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<td>19</td>
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<td>27</td>
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<td>% within Grade</td>
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<td>% of Total</td>
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</table>

Source of Existing Data
In the beginning of the fall 2004 semester and before any formal instruction had begun, students were asked to respond to a knowledge content test. Students were also given the Survey of Attitude toward Statistics, Test Anxiety Inventory, Motivation Inventory and the Survey of Experiences with Group Work. All surveys were delivered through an online course management system on the ANGEL (A New Global Environment for Learning) Web site.

Students engaged in all class activities as designed and scheduled by taking the readiness assessment tests, completing the lab quizzes, and working on group projects. Throughout the semester, students completed 13 lab quizzes, five individual and group readiness assessment tests, and three group work projects.

On the last day of class, a knowledge content test was again distributed to all of the students through the course’s ANGEL Web site. A time line for data collection during this semester when data were collected is provided in Table 3-2.

<table>
<thead>
<tr>
<th>Table 3-2: Time Line of Data Collection</th>
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<tbody>
<tr>
<td><strong>Week 2</strong></td>
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<tr>
<td><strong>Week 2 to Week 5</strong></td>
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<td><strong>Week 5</strong></td>
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<td><strong>Week 6</strong></td>
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<td><strong>Week 7</strong></td>
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<tr>
<td><strong>Week 10 to Week 13</strong></td>
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<td><strong>Week 14</strong></td>
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<td><strong>Week 15</strong></td>
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<tr>
<td><strong>Week 16</strong></td>
</tr>
</tbody>
</table>


As a result, all data gathered from this course consisted of surveys, course grades, and group information instruments as shown on Table 3-3. However, to test the ecological theory perspective of statistics performance model in this study, only two surveys and all parts of the course grade except for homework scores were selected.

### Table 3-3: Entire Data Set

**Surveys**
- Background Questionnaire
- Survey of Attitude toward Statistics*
- Motivation Inventory
- Test Anxiety Inventory
- Survey of Experience with Group Work*

**Course grades**
- Scores from Twelve Lab Quizzes*
- Scores from Three Group Problem Solving Activities*
- Scores from Five Individual and Group RATs*
- Scores from One Pre Knowledge Content Test
- Scores from One Posttest of Knowledge Content Test*
- Two Mid term Exams Scores*
- Final Exam Scores*
- Twelve Homework Scores

**Group Information**
- Group information
- Peer Assessment Assigned Group Information

*Note: Asterisk indicates data source was selected for this study.*

**Measurement Instruments**

The purpose of the two surveys and the six parts of the course grade was to measure the individual factor-attitudes toward statistics, the interpersonal factor-
experiences with group work, the reformed introductory course activities, and statistics performance.

The following observed variables from the existing data set were used to test the ecological theory perspective of statistics performance model: 28 survey items for the attitude latent variable (Survey of Attitude toward Statistics), 16 survey items for the experience with group work latent variable (Survey of Experience with Group Work), two observed variables for the degree of active engagement in the reformed course activities (Lab quizzes, Group projects with peer assessment), and four observed variables for the statistics performance latent variable (Readiness Assessment Tests, two mid-term exams, final exam, and knowledge content test). These latent and observed variables and their measured items are described in Table 3-4.
### Table 3-4: Latent and Observed Variables and Measured Items

<table>
<thead>
<tr>
<th>Variables</th>
<th>Assessed by</th>
<th>Measure description</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Individual Factor - Attitude toward Statistics</strong>&lt;br&gt;  - Affect&lt;br&gt;  - Cognitive competence&lt;br&gt;  - Value&lt;br&gt;  - Difficulty</td>
<td>Survey of Attitude toward Statistics</td>
<td>28 items</td>
<td>&lt;br&gt;  - 6 items : 7-point Likert&lt;br&gt;  - 6 items : 7-point Likert&lt;br&gt;  - 9 items : 7-point Likert&lt;br&gt;  - 7 items : 7-point Likert</td>
</tr>
<tr>
<td><strong>Interpersonal Factor - Experience with Group work</strong>&lt;br&gt;  - Confidence&lt;br&gt;  - Communication&lt;br&gt;  - Goals&lt;br&gt;  - Participation</td>
<td>Survey of Experience with Group Work</td>
<td>16 items</td>
<td>&lt;br&gt;  - 4 items : 5-point Likert&lt;br&gt;  - 4 items : 5-point Likert&lt;br&gt;  - 4 items : 5 point Likert&lt;br&gt;  - 4 items : 5-point Likert</td>
</tr>
<tr>
<td><strong>The Degree of Active Engagement in the Reformed Course Activities</strong>&lt;br&gt;  - Lab Quizzes&lt;br&gt;  - Group Projects with Peer Assessment</td>
<td>Lab Quizzes scores&lt;br&gt;  - Group Problem Solving Activities Scores</td>
<td>Average of 13 lab quizzes (drop lowest 2)&lt;br&gt;  - Sum of 3 group project scores</td>
<td>75 points&lt;br&gt;  - 200 points</td>
</tr>
<tr>
<td><strong>Statistics Performance</strong>&lt;br&gt;  - Readiness Assessment Tests&lt;br&gt;  - Exams&lt;br&gt;  - Final Exam&lt;br&gt;  - Knowledge Content Test</td>
<td>RATs scores&lt;br&gt;  - Two mid-term exam scores&lt;br&gt;  - Final exam scores&lt;br&gt;  - Post-knowledge content test scores</td>
<td>Average of 5 tests (drop lowest 1)&lt;br&gt;  - Total 200 points&lt;br&gt;  - Total 200 points&lt;br&gt;  - 24 items</td>
<td>240 points&lt;br&gt;  - 140 points&lt;br&gt;  - 200 points&lt;br&gt;  - 24 points</td>
</tr>
</tbody>
</table>
Individual Factor-Attitude toward Statistics

The Survey of Attitude toward Statistics (SATS)

The Survey of Attitude toward Statistics (SATS) (Hilton et al., 2004; Schau et al., 1995) is a 28-item instrument that measures four facets of college students’ attitude toward statistics: Affect, Cognitive competence, Value, and Difficulty.

1. Affect (six items): students’ positive and negative feelings about statistics.
2. Cognitive competence (six items): attitudes about the students’ intellectual knowledge and skills when applied to statistics.
3. Value (nine items): attitudes about the usefulness, relevance, and worth of statistics in personal and professional life.
4. Difficulty (seven items): attitudes about the difficulty of statistics as a domain.

The SATS has a 7-point Likert format anchored with the statement “Strongly Disagree” at the low end and “Strongly Agree” at the high end, and centered with the statement “Neither Agree nor Disagree.” Total composite scores on the SATS are formed by reversing the responses (1 becomes 7, 2 becomes 6, etc.) to the negative items indicated with an * in Table 4-13, and summing all scores on each factor. A higher score indicates a more positive attitude.

Coefficient alpha values ranged from .81 to .85 for affect, .77 to .85 for cognitive competence, .80 to .85 for value, and .64 to .77 for difficulty. Additional validity evidence was obtained through the correlation of the SATS with Wise’s Attitudes Toward Statistics scale (Wise, 1985), which showed significant, positive relationships between the two instruments (see Appendix E).
Interpersonal Factor—Experience with Group Work

*The Survey of Experience with Group Work*

The survey of Experience with Group Work measured students’ perceptions of how group work experience affected their learning. The Survey of Experience with Group Work was composed of four difference scales with a total of 16 items: confidence in group, communication, goals, and participation. These items were written by the Schreyer Institute for Teaching Excellence, and in part, adapted from other collaborative learning inventories (Cabrera et al., 2002; Crockett & Peter, 2003; Fenwick & Parsons, 1999; Millis & Cottell, 1998) to address the theoretical descriptions of collaborative learning by Johnson, Johnson, and Holubee (1991), and Salomon (1992). These items asked how much students valued and participated in collaborative learning in terms of their confidence, communication, goals, and participation.

The survey has a 5-point Likert format anchored with the statement “Strongly Disagree” at the low end and “Strongly Agree” at the high end, and centered with the statement “Neutral.” A higher total score indicates a more positive perception of group work.

The assessment of the confidence in group work consisted of four items from Cabrera et al.’s (2002) preference for collaborative learning instrument, tapping preferences towards learning in groups inside and outside the classroom. The reliability coefficient of this scale was .85 (Cabrera et al., 2002).
Communication of group work consisted of four items from the evaluation guide for cooperative learning (Fenwick & Parsons, 1999) and measured group members’ communication skill to support effective group work.

Goal for group work consisted of four items from the “clear goal and standard” subscale in the unit experience questionnaire developed by the Curtin Business School (Crockett & Peter, 2003). This subscale measures students’ perception of the clarity of the goals for group work.

Assessment of participation was created from four items from Millis and Cottell’s (1998) cooperative learning peer evaluation form. The cooperative learning evaluation form was used to determine those who have been active and cooperative members of the group as well as to identify those who did not participate. The original instrument was modified by changing the format to statements instead of questions (see Appendix F).

The Degree of Active Engagement in the Reformed Course Activities

The following reformed course activities were designed to actively engage of all students present. The degree of active engagement in the reformed course activities was measured by the participation in course activities in the lab quizzes, and the group projects with peer assessment. Both instruments were developed by the instructor, a domain expert who had more than 40 years’ field experience in statistics education and teaching experience in related courses at both graduate and undergraduate levels.
**Lab Quizzes**

Statistical problems in lab quizzes were assessments of students’ progress and applications, and simulations of statistical concepts, and the level of involvement in lab quizzes. There were 13 lab quizzes during the semester, and the score of each lab quiz could range from 1 to 100. The scores of lab quizzes were calculated by averaging the percentage of 11 lab quizzes after dropping the lowest two. The scores could range from 0 to 100, and were transformed to range from 0 to 75. The higher the scores on the quizzes meant that the student took more quizzes, and understood the concepts more than those with lower scores; therefore, it was interpreted as contributing to a higher degree of engagement.

**Group Project with Peer Assessment**

There were three group projects with peer assessment that assessed students’ comprehension on analyzing experimental data and discussing case studies. The instructor identified peer assessment criteria, and the researcher assisted him in its design and development. The scores of group projects with peer assessment were calculated by adding up three group project scores. The first project could range from 0 to 50, the second project could range from 0 to 100, and the third project could range from 0 to 100. After adding up the three projects’ scores, the scores were transformed to range from 0 to 200. This measure contributed to the degree of involvement in the group projects. The higher the scores on the group projects meant that the student was
participated more projects, and understood the concepts more than those with lower scores; therefore, it was interpreted as contributing to a higher degree of engagement.

Statistics Performance

Statistics performance assesses comprehension in students’ mastery of elementary statistical concepts, as measured by the readiness assessment test scores, two mid-term exams, the final exam, and the knowledge content test scores. All the instruments measuring statistics performance were developed by the instructor, a domain expert who had more than 40 years’ field experience in statistics education and teaching experience in related courses at both graduate and undergraduate levels.

Readiness Assessment Tests (RATs)

There were five readiness assessment tests during the semester to assess the understanding of the assigned reading and assignments before the class. The scores of readiness assessment tests were the sum of scores of the individual RATs and group RATs, and could range from 0 to 240. Individual and group RAT scores were calculated by average correct percentage of four RATs after dropping the lowest one, and could range from 0 to 100. The individual RAT scores were transformed to range from 0 to 160, and group RAT scores were transformed to range from 0 to 80 based on the instructor’s weighting of the grades.
Two Mid-term Exams

Two mid-term exams were designed to assess comprehension of statistical concepts covered in this course before each exam. Each exam was scored by using the percentage of correct answers and could range from 0 to 100. The sum of two midterm exam scores was 200 points, and these scores were changed to range from 0 to 140 points based on the instructor’s weighting of the grades.

Final Exam

The final exam was intended to assess the comprehension of statistical concepts covered in this course. The final exam was scored by using the percentage of correct answers and could range from 0 to 100.

Knowledge Content Test

This test contained 24 multiple-choice questions to assess comprehension in elementary statistical concepts. The content area of the test covered median, mean, distributions, percentiles, opinion polls/margin of error, population versus sample, interpreting results/proportions, confidence intervals/margin of error, percentiles/variability, sample size/standard error/large sample, and hypothesis testing/interpreting results/P-value/use of probability. The reliability coefficient of this knowledge content test was .72. The knowledge content test was scored by using the total number of correct answers and could range from 0 to 24 (see Appendix G).
Reliability and Validity of Constructs

Reliability tests using Cronbach’s alpha (\(\alpha\)) coefficient were conducted to examine the internal consistency of the measures. Reliability coefficients ranged from .712 to .916, suggesting these items measure the same theoretical construct (see Table 3-5).

<table>
<thead>
<tr>
<th></th>
<th>Number of Items</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attitude toward Statistics</td>
<td>28 items</td>
<td>.904</td>
</tr>
<tr>
<td>Affect</td>
<td>6 items</td>
<td>.808</td>
</tr>
<tr>
<td>Cognitive Competence</td>
<td>6 items</td>
<td>.852</td>
</tr>
<tr>
<td>Value</td>
<td>9 items</td>
<td>.840</td>
</tr>
<tr>
<td>Difficulty</td>
<td>7 items</td>
<td>.712</td>
</tr>
<tr>
<td>Experience of Group Work</td>
<td>16 items</td>
<td>.905</td>
</tr>
<tr>
<td>Confidence in Group</td>
<td>4 items</td>
<td>.820</td>
</tr>
<tr>
<td>Communication</td>
<td>4 items</td>
<td>.899</td>
</tr>
<tr>
<td>Goals</td>
<td>4 items</td>
<td>.812</td>
</tr>
<tr>
<td>Participation</td>
<td>4 items</td>
<td>.916</td>
</tr>
</tbody>
</table>

Because confirmatory factor analysis (CFA) focuses solely on the link between factors and their measured variables within the framework of Structural Equation Modeling, it represents what has been called a measurement model. In CFA, the reliability and validity can be assessed (Tate, 1998). The proportion of variance (\(R^2\)) is interpreted as the reliability of the measured variable in the analysis and as the proportion of variance in the variable that is accounted for by the factor. CFA is designed to test statistically whether the sample data are consistent with the imposed constraints between latent factors and indicators (Long, 1983). The result indicated that both instruments were reliable measures. These results are presented in Chapter 4.
Data Analysis

The primary method of statistical analysis was Structural Equation Modeling (SEM). SEM analysis tests hypotheses about relationships among observed and latent variables (Hoyle, 1995). SEM was used in this study to test for model fit as well as to provide information on statistics performance through an analysis of direct, indirect, and total effects (Kaplan, 2000). SEM provides a means of testing this model— it can determine if the model is plausible enough to account for the data. In addition, it provides the flexibility of including additional variables or specifying alternative formulations of the model (Miles & Shevlin, 2003).

Descriptive statistics, such as frequency distribution, means, standard deviations, skewness, and kurtosis, were used to describe the data using SPSS 12.0. The hypothesized model was tested using LISREL 8.5 and AMOS 4.0, with maximum likelihood estimation.

Standard SEM analysis steps were employed from Diamantopoulos and Siguaw (2000). These steps included: 1) Model Specification: Based on theory, experience, and the literature, the researcher specified a hypothesized model consisting of a network of direct causal links among the variables; 2) Model Identification: The identification of a model refers to the question of whether there is sufficient information (i.e., an adequate number of observed variances and covariances) to allow estimation of all of the model parameters; $t$-rule and rank condition were used for model identification; 3) Tests of Underlying Assumptions of SEM: A number of assumptions were tested in this study prior to analysis (outliers, normality, and multicollinearity); 4) Assessment of Model Fit: Confirmatory factor analysis for all latent variables with multiple indicators was
conducted, and SEM for the full structural model was evaluated, including an assessment of the overall fit of the model to the data; if a hypothesized model with acceptable fit is obtained, the component fit associated parameter is estimated; 5) **Model Modification:** If the model is not acceptable, the researcher may consider one or more revisions of the model based on theory and the modification indexes.

**Criteria for Model Specification**

The specification of the model is concerned with the development of theory-based hypotheses to serve as the guide for linking the latent variables (Diamantopoulos & Siguaw, 2000) and is a formal statement of one’s beliefs about the actual causal processes leading to the ultimate outcome (Tate, 1998). These beliefs would typically represent a synthesis of information from the research literature, various theories, and the opinions of others. The measurement and structural models for statistics performance in this study were conceptualized and specified based on ecological theory and the relevant empirical research on variables affecting statistics performance. Detailed information was provided in Chapter 1 (see Figure 1-3 and Figure 1-4).

**Criteria for Model Identification**

The identification of a model refers to the question of whether there is sufficient information (i.e., an adequate number of observed variances and covariances) to allow estimation of all of the model parameters (Kelloway, 1998; Tate, 1998). In order to obtain
a test of the overall model fit, the model must be overidentified. To test whether a model is overidentified, the $t$-rule is mostly employed in SEM.

The $t$-rule is a model of comparing the number of variances and covariances of the observed variables ($p(p+1)/2$, $p=$number of observed variables) with the number of model parameters to be estimated. To satisfy the $t$-rule, a model should provide equal or greater number of variances and covariances of the observed variables than the number of model parameters to be estimated. The model parameters to be estimated are the covariances of the latent variables, the number of factor loadings, and measurement error variances.

As is standard in SEM, circles or ellipses represent latent variables or constructs, squares or rectangles represent measured or observed variables, and single-headed arrows represent partialed causal paths. Circles with Ds represent disturbance terms on latent variables, and Es represent measurement errors in observed variables. Single-headed arrows between latent variables and observed variables represent factor loadings, while single-headed arrows between latent variables and observed variables represent regression coefficients or the impact of one variable on another. Finally, single-headed arrows joining disturbance terms or error terms with observed variables represent the impact of the residual or measurement error.

For the full model to be identified, the structural model must be identified. If the structural model is identified and can be estimated with observed data in practice, then the full model is identified. Therefore, the full model was reduced to the three most important variables of interest to the researcher—attitude, experience with group work, and statistics performance (see Figure 3-1), thereby keeping affect, cognitive competence,
values, difficulty, confidence, communication, goals, and participation variables as observed variables.

Figure 3-1: The ecological theory perspective of statistics performance model

In order to determine if the reduced structural model was underidentified, just-identified, or overidentified in this study, the degrees of freedom were again computed. The degrees of freedom were obtained by computing the difference between the number of data points and the number of estimated parameters in the hypothesized model or \( \frac{1}{2}(p)(p+1) - t \), where \( p \) is the number of observed variables and \( t \) is the number of parameters to be estimated (Kaplan, 2000).

This structural model included three latent variables (attitude, experience with group work, and statistics performance) and 14 observed variables (four observed variables for attitude latent variable, four observed variables for experience with group work, four observed variables for statistics performance, and two observed variables for group work experience).
work latent variables, two observed variables for the reformed introductory course activities, and four observed variables for statistics performance latent variable).

In this structural model, for those 14 observed variables there were 105 data points \[\frac{1}{2} (14)(14+1)=105\]. The number of parameters to be estimated included eight regression coefficients, 12 factor loadings, 14 error terms, three disturbance terms, and one covariance for a total of 38 parameter estimates. With 105 data points and 38 estimated parameters, this was an overidentified model with 67 degrees of freedom (105-38= 67). Therefore, this model was able to allow estimation of all of the model parameters in further analysis.

In establishing the identification of a full hypothesized model, the structural portion of the model, looking only at the relationships among the variables, must be identified (Kline, 1998). As above, the degrees of freedom were obtained by computing the difference between the number of data points and the number of estimated parameters in the hypothesized model (see Figure 3-2) or \[\frac{1}{2} \cdot (p)(p+1) - t\], where \(p\) is the number of observed variables and \(t\) is the number of parameters to be estimated (Kaplan, 2000). In this structural model, there were five observed variables for a total of 15 data points \[\frac{1}{2}(5)(5+1)=15\]. The number of parameters to be estimated included eight regression coefficients, two error terms, three disturbance terms, and one covariance for a total of 14 parameter estimates. With 15 data points and 14 estimated parameters, this was an overidentified model with one degree of freedom (15-14=1).
To establish modification, the $t$-rule is necessary but not sufficient for model identification (Kline, 1998). The rank condition will provide sufficient information for model identification. Evaluation of the rank condition was employed, and the rank condition was satisfied for every endogenous variable; therefore, the model is identified. Thus, this model was able to allow estimation of all of the model parameters in further analysis.
Tests of Underlying Assumptions of SEM

Once the model had been specified and identified, underlying assumptions of SEM were tested. Three key assumptions were tested in this study prior to completing the main analysis: (1) outliers (2) normality, and (3) multicollinearity.

Outliers. Outliers are the individual cases that have scores very different from others that can inappropriately influence the data (Schumacker & Lomax, 1996). A common rule of thumb is to define outliers as cases that are more than plus or minus three standard deviations from the mean of variables (Kline, 1998). Data transformations are recommended as a remedy for outliers (Tabachnick & Fidell, 1996). After the examination of outliers, some cases did have extreme values (i.e., lab quizzes and group project with peer assessment variables). Each case identified as an outlier was dealt with by individually changing this to the next most extreme value as recommended (Kline, 1998). 132 outliers (see Table 3-6) were found in each following observed variables: Attitude items (1, 4, 7, 10, 12, 13, 16, 18, 19, 23, 24), experience with group work items (9, 10, 11, 14), lab quizzes, group projects with peer assessment, final exam, and the knowledge content test.
If a case has extreme scores on two or more variables or its configuration of scores is unusual, it is called a multivariate outlier (Kline, 1998). Mahalanobis Distance (D2) is one of the statistics for finding multivariate outliers, indicating the multivariate distance between the scores of an individual case and the sample means (Tabachnick & Fidell, 1996). A squared Mahalanobis Distance value that significantly differs from 36.12 (the critical value of $\chi^2 (14)$ at the .001 level) indicates an outlier (Kline, 1998).

Multivariate outliers were not detected.

**Normality.** Each indicator of all 12 observed variables must be normally distributed. Non-normality can lead to several inaccurate conclusions regarding the model being tested (Byrne, 2001). *Skewness* and *kurtosis* are two ways that a distribution can be non-normal. Skewness greater than 3.00 is considered problematic (Kline, 1998). Similarly, kurtosis index values greater than 10 are considered problematic and values greater than 20 are more serious (Kline, 1998). Table 4-1, Table 4-4, and Table 4-9 provide descriptive statistics for measured variables.

<table>
<thead>
<tr>
<th>Table 3-6: Univariate Outliers</th>
<th>Number of Outliers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attitude item—4, 16, 23</td>
<td>4</td>
</tr>
<tr>
<td>Experience with group work items—9, 10, 11</td>
<td></td>
</tr>
<tr>
<td>Knowledge content test</td>
<td>5</td>
</tr>
<tr>
<td>Attitude item—4, 18, 24</td>
<td>7</td>
</tr>
<tr>
<td>Attitude item—1, 7, 12, 13, 19</td>
<td></td>
</tr>
<tr>
<td>Experience with group work item—14</td>
<td></td>
</tr>
<tr>
<td>Group projects with peer assessment</td>
<td></td>
</tr>
<tr>
<td>Final exam</td>
<td></td>
</tr>
<tr>
<td>Lab quizzes</td>
<td>18</td>
</tr>
</tbody>
</table>


In the original data set, the Lab Quizzes and Group Projects with Peer Assessment variables were not normally distributed. However, after the outliers’ data transformations, there were no problems with the normality of any variable. In this study, in order to determine if the data were non-normal, skewness and kurtosis were examined. All 12 observed variables reveal absolute values of skewness less than 2.0 and of kurtosis less than 10.0.

Multicollinearity. Another problem, multicollinearity, occurs when intercorrelations among some variables are too high. Multicollinearity causes nonpositive definite covariance matrices, which causes estimation to fail or the results to become unstable. If a Pearson correlation between two variables is more than .85, multicollinearity becomes prominent as these two variables measure the same thing. The Pearson correlations were conducted among all 12 observed variables and reviewed; high correlations could indicate a multicollinearity problem. None of the 12 observed variables was very highly correlated (see Appendix H in the correlation matrices), indicating this assumption was not violated in this study.

With missing data deleted and the outliers replaced, 249 cases remained and assumptions of normality and multicollinearity were satisfactory.

Criteria for Assessment of Model Fit

An important aspect of the evaluation of an estimated model is determining whether the model is consistent with, or fits, the empirical data (Tate, 1998). Tate (1998) provided two levels of the fit of the model to the data: 1) an overall fit assessment is
made using a consideration of several fit indices, and 2) component fit parameter estimates are made using the statistical significance, and the reasonableness of the parameter estimate.

In the overall fit assessment, numerous fit indices have been proposed and used to evaluate the quality of soundness of the measurement and structural parts of the model in terms of supporting theory-based hypotheses (Diamantopoulos & Siguaw, 2000), but thus far no one index has been found superior in all situations (Tate, 1998). Therefore, it is usually recommended that the results for a set of some of the more common indices be considered (Kelloway, 1998; Tate, 1998) including the chi-square statistics, the ratio of $\chi^2$ to the degree of freedom, the comparative fit index, the non-normed fit index, and the Root mean square error of approximation.

Because the goal is to develop a model that fits the data, a nonsignificant chi square is desired. If $\chi^2$ is not statistically significant at $p=.05$, the model fits the data. However, chi-square values depend of sample sizes; in models with large sample, trivial differences often cause the $\chi^2$ to be significant solely because of sample size (Tabachnick & Fidell, 1996). The chi-square statistic is heavily influenced by the sample size, and sample sizes that exceed 200 cases could be considered the large sample size (Kline, 1998). When the chi-square statistic is statistically significant, this suggests an inadequate fit. However, it should be noted that sample sizes that exceed 200, as in the present study, tend to increase the probability that the chi-square tests will yield statistical significance (Schumacker & Lomax, 1996). For this reason, many fit indices have been developed that assess model fit while eliminating or minimizing the effect of sample size. Therefore, Kline (1998) recommends reporting at least four fit indices. The
majority of researchers who utilize structural equation modeling techniques typically report several fit indexes simultaneously (Gerbing & Anderson, 1993) because there is “no single statistics test of significance that identifies a correct model given the sample data” (Schumacker & Lomax, 1996).

If the ratio of $\chi^2$ to the degree of freedom is equal to or less than two, it is typically taken to indicate a good fit.

The comparative fit index (CFI), proposed by Bentler (1990), is a measure of how much better the model fits compared to an independence model. The CFI ranges between 0 and 1, and values closer to 1 indicate a better fit to the data.

The non-normed fit index (NNFI), proposed by Bentler and Bonett (1980), is another measure of how much better the model fits compared to an independence model, and is one of the fit indexes less affected by sample size. The NNFI ranges from 0 to 1, and values closer to 1 indicate a better fit.

The final fit index used to estimate model fit in this study was the Root mean square error of approximation (RMSEA). The RMSEA was developed by Steiger (1990), and measures how closely the data is reflecting reality with smaller values indicating a better fit to the data. The RMSEA ranges from 0 to 1, and a value close to 0 indicates a good fit. However, Hu and Bentler (1999) recommended cutoff criteria for maximum likelihood estimation for model fit indices. The summary of model fit indices described above is presented in Table 3-7.
To briefly recapitulate, in this study, adequacy of model fit was assessed via the chi-square test. However, because this test is extremely sensitive to sample size (Bentler, 1990; Hu & Bentler, 1999; Schumacker & Lomax, 1996), four other fit indices were employed: the ratio of $\chi^2$ to the degree of freedom, the CFI, the NNFI, and the RMSEA.

Next the component fit parameter estimation allows one to test specific hypotheses. The significance and magnitude of the estimates revealed what factors significantly influence the statistics performance. This shows how precisely the value of the parameter has been estimated: The smaller the standard error, the better the estimate (Diamantopoulos & Siguaw, 2000). The test statistic is the $t$-statistic which represents the parameter estimate divided by its standard error. $|t| > 1.96$ indicate the parameter is significant at a .05 level (Byrne, 2001). The $t$-values are used in this study to determine whether a particular parameter is significantly different from zero in the population.

### Criteria for Model Modification

If the initial model were judged to be unacceptable in light of the results obtained in the assessment of model fit, the model would be examined to determine whether

<table>
<thead>
<tr>
<th>Model Fit Indices</th>
<th>Recommended Cutoff Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$/df</td>
<td>Less than 2.0</td>
</tr>
<tr>
<td>CFI</td>
<td>.95 or greater</td>
</tr>
<tr>
<td>NNFI</td>
<td>.95 or greater</td>
</tr>
<tr>
<td>RMSEA</td>
<td>Less than .06</td>
</tr>
</tbody>
</table>
model modification is necessary. Such model revisions would usually consist of the removal or addition of one or more paths to the initial model.

Modification indexes were examined to determine the existence of covariance between error terms and factors. This provides direction for improving the fit of the model to the data (Schumacker & Lomax, 1996). Modification index statistics represent the predicted estimated parameter changes of path coefficients and covariances for each fixed parameter in the model and yield important information regarding the sensitivity of the evaluation of fit to any reparameterization of the model (Byrne, 2001). Thus, the absence of any large modification indexes would be a model that is judged acceptable in the empirical model evaluation (Tate, 1998). In addition, large modification indexes suggest that the model fit could be improved by revision.

In this study, taking into account the feasibility and statistical significance of all parameter estimates and the substantially good fit of the model, the modification index was carefully reviewed to determine whether the fit of the model could be meaningfully improved by allowing covariation between factors or error terms. Only those covariations that made any substantive and theoretical sense were used.

Summary

This chapter presented a description of the methods used in this study. A total of 249 students’ data obtained from a 2004 fall semester introductory statistics course were used in this study. To test the ecological theory perspective of statistics performance model in this study, the survey of Attitude toward Statistics, the Survey of Experience
with Group Work, and six parts of course grades were used from the existing data set. Data analysis for this study was done using Structural Equation Modeling (SEM) techniques and consisted of five steps based on the common procedures of analyzing data in SEM provided by Diamantopoulos and Siguaw (2000). The analytic strategies in each step from 1 to 3 were described in this chapter. (Please note that results of assessment of model fit of measurement and structural models for statistics performance based on step 4 and 5 are presented in the next chapter.)

First, the measurement and structural models for statistics performance in this study were conceptualized and specified based on ecological theory perspective and the relevant empirical research on variables affecting statistics performance. Detailed information was provided in Chapter 1 (see Figure 1-3 and Figure 1-4). Second, the structural model for statistics performance in this study was overidentified by the $t$-rule and rank condition. Third, underlying assumptions for SEM were tested for this study. Afterward, investigations found no univariate/multivariate outliers. In addition, multivariate normality was sustained.

Fourth, tests of measurement and structural models for statistics performance in this study by the overall fit of the model were conducted, as detailed in Chapter 4. Five fit indices were employed for the overall fit test including the chi-square test, the $\chi^2/df$, the CFI, the NNFI, and the RMSEA and the significance of the parameters. Finally, the modification indexes were carefully reviewed to determine whether the fit of the model could be meaningfully improved by allowing covariation between error terms. Only those covariations that made any substantive and theoretical sense were used.
Chapter 4

RESULTS

The main purpose of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance. In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance. In order to determine how well the conceptual model explained the statistics performance, the following questions were investigated:

- Does ecological theory explain statistics performance and is the model that is built on this framework consistent with the data?
- Are the identified predictor variables (the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and the degree of active engagement of the reformed course activities) significant predictors of statistical performance?
• What are the direct, indirect, and total effects of the identified predictor variables on the statistical performance?

This study used Structural Equation Modeling (SEM) analyses to test the hypothesized conceptual model. Data analysis consisted of five steps based on the common procedures of analyzing data in SEM provided by Diamantopoulos and Siguaw (2000). A full description of the analytic strategies in each step from 1 to 3 was described in Chapter 3.

The fourth step of the data analysis, Assessment of Model Fit, employed the two-step approach recommended by Anderson and Gerbing (1988). The results of the assessment of model fit and model modification are presented in this chapter. First, three confirmatory factor analyses (the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and statistics performance) were conducted to describe how well the observed indicators served as a measurement instrument for the latent variables. The first section presents the results of the measurement models, including three confirmatory factor analyses.

Then, if an acceptable measurement model is found according to the criteria, a hypothesized full structural equation model (the ecological theory perspective of statistics performance model) with latent variables is tested to assess hypothesized causal links among the latent variables. The results of the full ecological theory perspective of statistics performance structural model are reported in the second section. Finally, results of the hypothesis testing are summarized.

Figure 4-1 shows the hypothesized conceptual model. Two of the independent variables (the individual factor-attitude towards statistics and the interpersonal factor-
experience with group work) are exogenous variables, while the two independent variables (lab quizzes, and group projects) are posited as mediating variables. The dependent variable, statistics performance, is an endogenous variable.

Analysis of the Three Measurement Models

This study proposed three measurement models: the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and statistics performance. Each measurement model was analyzed with confirmatory factor analysis (CFA). In CFA, the relationships (factor loadings) between the four observed variables and each latent variable were interpreted as factor loadings (regression coefficients).
(Kline, 1998). The model test was based on their covariance matrix and used maximum likelihood estimation as implemented in LISREL 8.7. One variable per latent variables is fixed to equal 1.0, which sets the scale and simplifies solution of the identification problem (Lomax, 1982).

Testing each measurement model independently allowed the researcher to assure construct validity and modify any measurement model that was insufficient, prior to testing the full model (Byrne, 2001).

**The Individual Factor-Attitude toward Statistics**

Confirmatory factor analysis was performed on the four factors for the individual factor-attitude toward statistics measurement model. Descriptive statistics are presented in Table 4-1, and correlations between the four observed variables for attitude toward statistics are presented in Appendix H.
Table 4-1: Descriptive Statistics of the Individual Factor-Attitude toward Statistics

<table>
<thead>
<tr>
<th>Affect</th>
<th>Range</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I will like statistics.</td>
<td>3</td>
<td>4.26</td>
<td>.955</td>
<td>.269</td>
<td>-.862</td>
</tr>
<tr>
<td>2*. I will feel insecure when I have to do statistics problems.</td>
<td>6</td>
<td>4.35</td>
<td>1.538</td>
<td>-.138</td>
<td>-.958</td>
</tr>
<tr>
<td>11*. I will get frustrated going over statistics tests in class.</td>
<td>6</td>
<td>4.41</td>
<td>1.609</td>
<td>-.162</td>
<td>-.825</td>
</tr>
<tr>
<td>14*. I will be under stress during statistics class.</td>
<td>6</td>
<td>3.76</td>
<td>1.568</td>
<td>.267</td>
<td>-.732</td>
</tr>
<tr>
<td>15. I will enjoy taking statistics courses.</td>
<td>6</td>
<td>3.81</td>
<td>1.245</td>
<td>-.054</td>
<td>-.242</td>
</tr>
<tr>
<td>21*. I am scared by statistics.</td>
<td>6</td>
<td>4.43</td>
<td>1.824</td>
<td>-.142</td>
<td>-1.075</td>
</tr>
<tr>
<td>Cognitive competence</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3*. I will have trouble understanding statistics because of how I think.</td>
<td>6</td>
<td>4.49</td>
<td>1.535</td>
<td>-.193</td>
<td>-.862</td>
</tr>
<tr>
<td>9*. I will have no idea of what's going on in statistics.</td>
<td>6</td>
<td>4.98</td>
<td>1.496</td>
<td>-.563</td>
<td>-.313</td>
</tr>
<tr>
<td>20*. I will make a lot of math errors in statistics.</td>
<td>6</td>
<td>4.36</td>
<td>1.499</td>
<td>-.143</td>
<td>-.519</td>
</tr>
<tr>
<td>23. I can learn statistics.</td>
<td>5</td>
<td>5.91</td>
<td>1.111</td>
<td>-.212</td>
<td>1.665</td>
</tr>
<tr>
<td>24. I will understand statistics equations.</td>
<td>3</td>
<td>5.39</td>
<td>.941</td>
<td>.194</td>
<td>-.833</td>
</tr>
<tr>
<td>27*. I will find it difficult to understand statistics concepts.</td>
<td>6</td>
<td>4.38</td>
<td>1.446</td>
<td>-.342</td>
<td>-.528</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5*. Statistics is worthless.</td>
<td>5</td>
<td>5.76</td>
<td>1.278</td>
<td>-1.160</td>
<td>.874</td>
</tr>
<tr>
<td>7. Statistics should be a required part of my professional training.</td>
<td>3</td>
<td>4.57</td>
<td>1.064</td>
<td>-.095</td>
<td>-1.218</td>
</tr>
<tr>
<td>8. Statistical skills will make me more employable.</td>
<td>6</td>
<td>5.07</td>
<td>1.335</td>
<td>-.710</td>
<td>.717</td>
</tr>
<tr>
<td>10*. Statistics is not useful to the typical professional.</td>
<td>3</td>
<td>5.53</td>
<td>1.032</td>
<td>-.103</td>
<td>-1.131</td>
</tr>
<tr>
<td>12*. Statistical thinking is not applicable in my life outside my job.</td>
<td>3</td>
<td>5.46</td>
<td>1.039</td>
<td>.037</td>
<td>-1.161</td>
</tr>
<tr>
<td>13. I use statistics in my everyday life.</td>
<td>3</td>
<td>4.49</td>
<td>1.074</td>
<td>-.033</td>
<td>-1.253</td>
</tr>
<tr>
<td>16*. Statistics conclusions are rarely presented in everyday life.</td>
<td>3</td>
<td>5.59</td>
<td>1.036</td>
<td>-.211</td>
<td>-1.107</td>
</tr>
<tr>
<td>19*. I will have no application for statistics in my profession.</td>
<td>3</td>
<td>5.67</td>
<td>1.030</td>
<td>-.288</td>
<td>-1.045</td>
</tr>
<tr>
<td>25*. Statistics is irrelevant in my life.</td>
<td>5</td>
<td>5.57</td>
<td>1.278</td>
<td>-.927</td>
<td>.416</td>
</tr>
<tr>
<td>Difficulty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Statistics formulas are easy to understand.</td>
<td>3</td>
<td>4.39</td>
<td>1.038</td>
<td>.113</td>
<td>-1.152</td>
</tr>
<tr>
<td>6*. Statistics is a complicated subject.</td>
<td>6</td>
<td>3.62</td>
<td>1.392</td>
<td>.247</td>
<td>-.516</td>
</tr>
<tr>
<td>17. Statistics is a subject quickly learned by most people.</td>
<td>5</td>
<td>3.17</td>
<td>1.176</td>
<td>.163</td>
<td>-.402</td>
</tr>
<tr>
<td>18*. Learning statistics requires a great deal of discipline.</td>
<td>3</td>
<td>3.35</td>
<td>1.005</td>
<td>.178</td>
<td>-1.041</td>
</tr>
<tr>
<td>22*. Statistics involves massive computations.</td>
<td>6</td>
<td>4.67</td>
<td>1.324</td>
<td>-.246</td>
<td>-.100</td>
</tr>
<tr>
<td>26*. Statistics is highly technical.</td>
<td>6</td>
<td>4.09</td>
<td>1.147</td>
<td>.230</td>
<td>-.211</td>
</tr>
<tr>
<td>28*. Most people have to learn a new way of thinking to do statistics.</td>
<td>6</td>
<td>3.97</td>
<td>1.181</td>
<td>.151</td>
<td>.108</td>
</tr>
</tbody>
</table>

Note: Responses were coded as using 7-point Likert scale (1: strongly disagree, and 7: strongly agree), and reversing the responses (1 becomes 7, 2 becomes 6, etc.) to the items indicated with an asterisk.
The measurement model showed that each latent factor was represented by 28 indicators. The four factors that emerged from the factor analysis related to affect, cognitive competence, value, and difficulty. Affect was comprised of six items, cognitive competence was comprised of six items, value was comprised of nine items, and difficulty was comprised of seven items.

The test of the measurement model obtained a significant chi-square ($\chi^2 = 863.74, \text{df}=347, p=.000$), the ratio of chi-square to degrees of freedom is greater than 2.0 ($\chi^2/\text{df}=2.48$), the CFI (.94) and the NNFI (.94) are less than .95, and the RMSEA (.077) is greater than .06 (see Table 4-2).

| Table 4-2: Fit Indices of the Individual Factor-Attitude toward Statistics |
|-----------------|-----|-------|------|-----|-------|
|                 | $\chi^2$ | df   | $\chi^2/\text{df}$ | CFI  | NNFI  | RMSEA |
| Original Model  | 863.74   | 347  | 2.489          | .94  | .93   | .077  |
| Modified Model  | 642.25   | 343  | 1.872          | .96  | .96   | .059  |

Thus, the fit indices indicated that the measurement model for the individual factor-attitude toward statistics was acceptable. However, review of the modification indexes suggested that allowing the error terms to covary could improve the model.

A careful review of the modification indexes suggests whether the fit of the model could be meaningfully improved by allowing covariation between factors and error terms. These error terms were allowed to covary since each pair was worded similarly and it seemed reasonable that they might share certain similar measurement errors (see Figure 4-2). Only those covariations that made any substantive and
theoretical sense were used. It seems plausible that students who like statistics enjoy
taking statistics courses more, so this covariance was added. Also, it seems plausible that
students who understand statistics tend to be more confident about learning statistics,
and that students who think statistics should be part of professional training endorse
more the idea that statistics skills make them employable. It is also plausible that
students who believe statistics is computations associate more with the technical
perspective, especially when students use software and other tools. So those
measurement errors associated with “item 1” and “item 15,” “item 23” and “item 24,”
“item 7” and “item 8,” and “item 22” and “item 26” were added.

All criteria used indicated an adequate fit of the theoretical data to the model \[ \chi^2 = 642.25, \text{df}=343, p=.000; \chi^2/\text{df}=1.872; \text{CFI}=.96; \text{NNFI}=.96; \text{RMSEA}=.059 \] (see Table 4-2). The chi-square statistic was statistically significant, which suggests an inadequate fit. However, it should be noted that sample sizes that exceed 200, as in the present study, tend to increase the probability that the chi-square tests will yield statistical significance (Schumacker & Lomax, 1996). Further, the ratio of chi-square to degrees of freedom (1.872) was well below the cutoff criterion of adequate fit of 2 to 1 recommended by most researchers (e.g., Byrne, 1989). Also, all other goodness-of-fit measures reported above were much greater than the cutoff points of .95 (e.g., Bentler & Bonett, 1980; Hu & Bentler, 1995) that have been recommended by researchers for demonstrating model adequacy. Finally, the RMSEA was less than .06, suggesting that there was a good fit of the model (Hu & Bentler, 1999). The combination of these indices suggested that the modified model provided a good explanation of the data.
Also, the parameter estimates were interpretable. Table 4-3 shows standardized parameter estimates and squared multiple correlations for each latent variable. All
estimates were statistically significant \((p<.05)\), and it could be concluded that all 28 items are a significant indicator of attitude toward the statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Path coefficients</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affect</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PREA21</td>
<td>.88*</td>
<td>0.78</td>
</tr>
<tr>
<td>PREA15</td>
<td>.53*</td>
<td>0.28</td>
</tr>
<tr>
<td>PREA14</td>
<td>.73*</td>
<td>0.53</td>
</tr>
<tr>
<td>PREA11</td>
<td>.57*</td>
<td>0.33</td>
</tr>
<tr>
<td>PREA02</td>
<td>.61*</td>
<td>0.37</td>
</tr>
<tr>
<td>PREA01</td>
<td>.43*</td>
<td>0.19</td>
</tr>
<tr>
<td>Cognitive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PREA27</td>
<td>.82*</td>
<td>0.67</td>
</tr>
<tr>
<td>PREA24</td>
<td>.63*</td>
<td>0.40</td>
</tr>
<tr>
<td>PREA23</td>
<td>.65*</td>
<td>0.42</td>
</tr>
<tr>
<td>PREA20</td>
<td>.57*</td>
<td>0.33</td>
</tr>
<tr>
<td>PREA09</td>
<td>.71*</td>
<td>0.50</td>
</tr>
<tr>
<td>PREA03</td>
<td>.73*</td>
<td>0.53</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PREA25</td>
<td>.67*</td>
<td>0.45</td>
</tr>
<tr>
<td>PREA19</td>
<td>.73*</td>
<td>0.54</td>
</tr>
<tr>
<td>PREA16</td>
<td>.61*</td>
<td>0.37</td>
</tr>
<tr>
<td>PREA13</td>
<td>.47*</td>
<td>0.22</td>
</tr>
<tr>
<td>PREA12</td>
<td>.68*</td>
<td>0.46</td>
</tr>
<tr>
<td>PREA10</td>
<td>.66*</td>
<td>0.43</td>
</tr>
<tr>
<td>PREA08</td>
<td>.55*</td>
<td>0.30</td>
</tr>
<tr>
<td>PREA07</td>
<td>.51*</td>
<td>0.26</td>
</tr>
<tr>
<td>PREA05</td>
<td>.55*</td>
<td>0.30</td>
</tr>
<tr>
<td>Difficulty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PREA28</td>
<td>.51*</td>
<td>0.26</td>
</tr>
<tr>
<td>PREA26</td>
<td>.36*</td>
<td>0.13</td>
</tr>
<tr>
<td>PREA22</td>
<td>.50*</td>
<td>0.25</td>
</tr>
<tr>
<td>PREA18</td>
<td>.36*</td>
<td>0.13</td>
</tr>
<tr>
<td>PREA17</td>
<td>.29*</td>
<td>0.09</td>
</tr>
<tr>
<td>PREA06</td>
<td>.59*</td>
<td>0.35</td>
</tr>
<tr>
<td>PREA04</td>
<td>.60*</td>
<td>0.36</td>
</tr>
</tbody>
</table>

\* \(p<.05\)

The Interpersonal Factor-Experience with Group Work

Confirmatory factor analysis was performed on the four factors for the interpersonal factor-experience with group measurement model. Descriptive statistics
are presented in Table 4-4, and correlations for the interpersonal factor-experience with group work variables are presented in Appendix H.

| Table 4-4: Descriptive Statistics of the Interpersonal Factor-Experience with Group Work |
|--------------------------------------------------|--------|--------|--------|--------|--------|
| **Confidence in group**                          | Range | Mean   | SD     | Skewness | Kurtosis |
| 1. I felt that I learned better when students taught each other rather than having instructors. | 3     | 2.45   | 1.069  | .022     | -1.244  |
| 2. I preferred learning in groups with other students to learning from lectures. | 4     | 2.88   | 1.311  | .008     | -1.109  |
| 3. I learned best when I was required to work collaboratively with other students on course assignments. | 4     | 2.78   | 1.305  | .112     | -1.060  |
| 4. I learned a great deal when I studied in groups outside of class. | 4     | 2.86   | 1.259  | -.018    | -1.048  |
| **Communication**                                |       |        |        |          |         |
| 5. All group members shared their ideas freely.  | 4     | 3.55   | 1.257  | -.603    | -.609   |
| 6. My group members offered support and encouragement to each other. | 4     | 3.64   | 1.230  | -.706    | -.414   |
| 7. My group members asked each other questions to make sure everyone understood the ideas and information we were working with. | 4     | 3.59   | 1.208  | -.659    | -.441   |
| 8. My group was energetic. We welcomed new ideas, showed enthusiasm, and laughed with each other. | 4     | 3.52   | 1.280  | -.471    | -.886   |
| **Goals**                                        |       |        |        |          |         |
| 9. It was always easy to know the goals of group projects expected. | 3     | 3.48   | 1.093  | -.009    | -1.300  |
| 10. My group members usually had a clear idea of where we were going and what was expected of us in group projects. | 3     | 3.54   | 1.081  | -.157    | -1.251  |
| 11. It was not often hard to discover what was expected of us in group projects. | 3     | 3.42   | 1.037  | .003     | -1.176  |
| 12. The faculty made it clear right from the start what was expected of students. | 4     | 2.94   | 1.264  | -.103    | -.951   |
| **Participation**                                |       |        |        |          |         |
| 13. My group members have attended the group meeting scheduled during the class time. | 4     | 4.02   | 1.122  | -1.190   | .885    |
| 14. My group members made an effort at assigned projects. | 2     | 4.26   | .808   | -.510    | -1.287  |
| 15. My group members attempted to make contributions and/or seek help within the group when we need it. | 4     | 3.94   | 1.152  | -1.101   | .542    |
| 16. My group members cooperated with group effort. | 4     | 4.01   | 1.185  | -1.145   | .469    |

Using 5-point Likert scale (1: strongly disagree, and 5: strongly agree)
For this experience with group work variable, exploratory factor analysis was initially performed on all 16 items in the interpersonal factor-experience with group work, because the survey of Experience with Group Work has not been tested empirically. The survey of Experience with Group Work measured students’ perceptions of how group work experience affects students’ learning. The 16-item scale was subjected to exploratory factor analysis forcing four factors based upon the four dimensions hypothesized to be represented; (1) confidence in group work, (2) communication of group work, (3) goal for group work, and (4) participation. The results of the exploratory factor analysis indicated the four-factor solution with oblimin rotation was acceptable. All items loaded cleanly on four factors (see Table 4-5).

<table>
<thead>
<tr>
<th></th>
<th>Participation</th>
<th>Confidence</th>
<th>Goal</th>
<th>Communication</th>
</tr>
</thead>
<tbody>
<tr>
<td>EGroup14</td>
<td>.946</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td>EGroup13</td>
<td>.879</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td>EGroup15</td>
<td>.830</td>
<td>.002</td>
<td>.002</td>
<td>-.129</td>
</tr>
<tr>
<td>EGroup16</td>
<td>.650</td>
<td>.002</td>
<td>.002</td>
<td>-.361</td>
</tr>
<tr>
<td>EGroup02</td>
<td>.102</td>
<td>.840</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td>EGroup03</td>
<td>.002</td>
<td>.783</td>
<td>.002</td>
<td>-.208</td>
</tr>
<tr>
<td>EGroup01</td>
<td>.002</td>
<td>.767</td>
<td>.002</td>
<td>.173</td>
</tr>
<tr>
<td>EGroup04</td>
<td>.002</td>
<td>.753</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td>EGroup11</td>
<td>.002</td>
<td>.002</td>
<td>.877</td>
<td>.002</td>
</tr>
<tr>
<td>EGroup12</td>
<td>.002</td>
<td>.002</td>
<td>.785</td>
<td>.112</td>
</tr>
<tr>
<td>EGroup09</td>
<td>.002</td>
<td>.002</td>
<td>.669</td>
<td>-.321</td>
</tr>
<tr>
<td>EGroup10</td>
<td>.329</td>
<td>.002</td>
<td>.590</td>
<td>-.136</td>
</tr>
<tr>
<td>EGroup07</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
<td>-.858</td>
</tr>
<tr>
<td>EGroup08</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
<td>-.824</td>
</tr>
<tr>
<td>EGroup05</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
<td>-.812</td>
</tr>
<tr>
<td>EGroup06</td>
<td>.141</td>
<td>.002</td>
<td>.002</td>
<td>-.787</td>
</tr>
</tbody>
</table>

The test of the measurement model obtained a significant chi-square ($\chi^2=219.71$, $df=100$, $p=.000$), the ratio of chi-square to degrees of freedom was greater than 2.0
(χ²/df=2.19), and the RMSEA (.69) was greater than .06. The CFI was .98 and the NNFI was .97.

The fit indices indicated that the measurement model for the interpersonal factor-experience with group work had an acceptable fit of the data. However, review of the modification indexes suggested that allowing the error terms to covary could improve the model.

| Table 4-6: Fit Indices of the Interpersonal Factor-Experience with Group Work |
|---|---|---|---|---|---|
|       | χ²  | df  | χ²/df | CFI  | NNFI | RMSEA  |
| Original Model | 219.71 | 100 | 2.19  | .98  | .97  | .069   |
| Modified Model  | 181.04 | 97  | 1.86  | .97  | .98  | .059   |

A careful review of the modification indexes suggests whether fit of the model could be meaningfully improved by allowing covariation between factors or error terms. Careful consideration was given to modification indexes that suggested allowing the error terms between “asked each other questions to make sure everyone understood the ideas and information” and “welcomed new ideas, showed enthusiasm,” “not often hard to discover what was expected” and “made it clear right from the start what was expected,” and “have attended the group meeting” and “made an effort at assigned projects” to covary. This made intuitive sense. Those questions ask for conceptual information and it is possible that their error terms shared some variance. Thus, the covariances between these error terms were included in the modified model (see Figure 4-3).
The fit indices for the modified model $[\chi^2=181.04, \text{df}=97, p=.000; \chi^2/\text{df}=1.86; \text{CFI}=0.97; \text{NFI}=0.98; \text{RMSEA}=0.059]$ indicated a significantly better fit (see Table 4-6). The interpersonal factor-experience with group work as measured by the four factors are well-supported by the data.

Figure 4-3: Estimated parameters for the interpersonal factor-experience with group work modified model
Table 4-7 contains standardized parameter estimates and squared multiple correlations for each latent variable. All estimates of each observed variable to underlying latent variables were statistically significant (p<.05), and it could be concluded that all 16 items were a significant indicators of experience with group work.

Table 4-7: Standardized Factor Loading for the Interpersonal Factor-Experience with Group Work Modified Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Path coefficients</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence in group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 01</td>
<td>.50*</td>
<td>.25</td>
</tr>
<tr>
<td>Group 02</td>
<td>.85*</td>
<td>.72</td>
</tr>
<tr>
<td>Group 03</td>
<td>.85*</td>
<td>.73</td>
</tr>
<tr>
<td>Group 04</td>
<td>.72*</td>
<td>.52</td>
</tr>
<tr>
<td>Communication</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 05</td>
<td>.77*</td>
<td>.60</td>
</tr>
<tr>
<td>Group 06</td>
<td>.87*</td>
<td>.76</td>
</tr>
<tr>
<td>Group 07</td>
<td>.84*</td>
<td>.71</td>
</tr>
<tr>
<td>Group 08</td>
<td>.81*</td>
<td>.65</td>
</tr>
<tr>
<td>Goals</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 09</td>
<td>.81*</td>
<td>.65</td>
</tr>
<tr>
<td>Group 10</td>
<td>.83*</td>
<td>.69</td>
</tr>
<tr>
<td>Group 11</td>
<td>.75*</td>
<td>.57</td>
</tr>
<tr>
<td>Group 12</td>
<td>.42*</td>
<td>.18</td>
</tr>
<tr>
<td>Participation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 13</td>
<td>.75*</td>
<td>.56</td>
</tr>
<tr>
<td>Group 14</td>
<td>.81*</td>
<td>.65</td>
</tr>
<tr>
<td>Group 15</td>
<td>.92*</td>
<td>.84</td>
</tr>
<tr>
<td>Group 15</td>
<td>.90*</td>
<td>.82</td>
</tr>
</tbody>
</table>

* p<.05
Statistics Performance

Confirmatory factor analysis was performed on the observed variables for the statistics performance measurement model. Descriptive statistics are presented in Table 4-8, and correlations between the four observed variables for statistics performance are presented in Appendix H.

<table>
<thead>
<tr>
<th>Table 4-8: Descriptive Statistics of Statistics Grade</th>
<th>Range</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Readiness Assessment tests</td>
<td>79.80</td>
<td>208.31</td>
<td>17.93</td>
<td>-.405</td>
<td>-.433</td>
</tr>
<tr>
<td>Two Midterm Exams</td>
<td>77.00</td>
<td>112.17</td>
<td>16.50</td>
<td>-.300</td>
<td>-.404</td>
</tr>
<tr>
<td>Final Exam</td>
<td>80.00</td>
<td>163.59</td>
<td>20.79</td>
<td>-.592</td>
<td>-.486</td>
</tr>
<tr>
<td>Knowledge Content Test</td>
<td>13.00</td>
<td>17.05</td>
<td>3.11</td>
<td>-.516</td>
<td>-.334</td>
</tr>
</tbody>
</table>

The measurement model showed that statistics performance was represented by four indicators. The test of the measurement model obtained nonsignificant chi-square ($\chi^2=5.78$, $df=2$, $p=.055$), the ratio of chi-square to degrees of freedom was greater than 2.0 ($\chi^2/df=2.89$), the CFI (.99) and the NNFI (.97) were greater than .95, and the RMSEA (.087) was greater than .06 (see Table 4-9).

<table>
<thead>
<tr>
<th>Table 4-9: Fit Indices of the Statistics Performance</th>
<th>$\chi^2$</th>
<th>df</th>
<th>$\chi^2/df$</th>
<th>CFI</th>
<th>NNFI</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Model</td>
<td>5.78</td>
<td>2</td>
<td>2.89</td>
<td>.99</td>
<td>.97</td>
<td>.087</td>
</tr>
<tr>
<td>Modified Model</td>
<td>.346</td>
<td>1</td>
<td>.346</td>
<td>1.00</td>
<td>.99</td>
<td>.000</td>
</tr>
</tbody>
</table>
Thus, the fit indices indicated that the measurement model for the statistics performance was acceptable. However, review of the modification indexes suggested that allowing the error terms to covary could improve the model.

A careful review of the modification indexes suggests whether the fit of the model could be meaningfully improved by allowing covariation between error terms. The measurement error associated with “final exam” and “the knowledge content test” was allowed to covary. RATs and two midterm exams were designed to assess the comprehension of the statistical concepts, and covered specific topics based on assigned readings and topics that had been taught. However, the final exam and the knowledge content test were also designed to assess comprehension of the statistical concepts, and both tests were given to students at the end of the semester as an overall assessment. So it seemed reasonable that they might share certain variance (see Figure 4-4).

---

Figure 4-4: Estimated parameters for the statistics performance modified model
All criteria used indicated an adequate fit of the theoretical data to the model \( \chi^2 \) = .346, \( \text{df}=1, \ p=.556; \ \chi^2/\text{df}=.346; \ \text{CFI}=1.00; \ \text{NNFI}=.99; \ \text{RMSEA}=.000 \) (see Table 4-9). The chi-square statistic was not statistically significant, which suggests a good fit. Further, the ratio of chi-square to degrees of freedom (.346) was well below the cutoff criterion of adequate fit of 2 to 1 recommended by most researchers (e.g., Byrne, 1989). Also, all other goodness-of-fit measures reported above were much greater than the cutoff points of .95 (e.g., Bentler & Bonett, 1980; Hu & Bentler, 1995) that have been recommended by researchers for demonstrating model adequacy. Finally, the RMSEA was less than .06, suggesting that there was a good fit of the model (Hu & Bentler, 1999). The combination of these indices suggested that the modified model provided a good explanation of the data.

Also, the parameter estimates were interpretable. Table 4-10 shows standardized parameter estimates and squared multiple correlations for each latent variable. All estimates were statistically significant (\( p<.05 \)), and it could be concluded that all four indicators are a significant indicator of statistics performance.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Path coefficients</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>RATs</td>
<td>.766*</td>
<td>.60</td>
</tr>
<tr>
<td>Exams</td>
<td>.965*</td>
<td>.90</td>
</tr>
<tr>
<td>Final Exam</td>
<td>.692*</td>
<td>.50</td>
</tr>
<tr>
<td>Knowledge Content Test</td>
<td>.420*</td>
<td>.19</td>
</tr>
</tbody>
</table>

* \( p<.05 \)

Thus, the confirmatory factor analyses of the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and statistics
performance were found acceptable so that the study could proceed to the testing of the structural model.

**Initial Hypothesized Structural Model**

Having established the best fitting measurement models for the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and the statistics performance, the hypothesized structural model was performed on the ecological theory perspective of statistics performance model. Descriptive statistics are presented in Table 4-11, and correlations for the statistics performance variables are presented in Appendix H. The model test was based on the covariance matrix and used maximum likelihood estimation as implemented in AMOS 4.0 and described in Chapter 3.

**Table 4-12: Descriptive Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Range</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affect</td>
<td>32.00</td>
<td>25.02</td>
<td>6.33</td>
<td>.056</td>
<td>-.439</td>
</tr>
<tr>
<td>Cognitive</td>
<td>31.00</td>
<td>29.52</td>
<td>6.08</td>
<td>-.191</td>
<td>-.238</td>
</tr>
<tr>
<td>Value</td>
<td>32.00</td>
<td>27.25</td>
<td>5.04</td>
<td>.127</td>
<td>.394</td>
</tr>
<tr>
<td>Difficulty</td>
<td>32.00</td>
<td>47.72</td>
<td>6.73</td>
<td>-.301</td>
<td>-.372</td>
</tr>
<tr>
<td>Confidence</td>
<td>15.00</td>
<td>10.97</td>
<td>4.01</td>
<td>-.098</td>
<td>-.783</td>
</tr>
<tr>
<td>Communication</td>
<td>16.00</td>
<td>14.30</td>
<td>4.35</td>
<td>-.651</td>
<td>-.391</td>
</tr>
<tr>
<td>Goals</td>
<td>13.00</td>
<td>13.38</td>
<td>3.55</td>
<td>.043</td>
<td>-.752</td>
</tr>
<tr>
<td>Participation</td>
<td>14.00</td>
<td>16.23</td>
<td>3.81</td>
<td>-.923</td>
<td>.106</td>
</tr>
<tr>
<td>Lab Quizzes</td>
<td>4.91</td>
<td>73.85</td>
<td>.66</td>
<td>1.319</td>
<td>.367</td>
</tr>
<tr>
<td>Group Projects with Peer Assessment</td>
<td>28.00</td>
<td>184.54</td>
<td>7.20</td>
<td>-.598</td>
<td>-.238</td>
</tr>
<tr>
<td>Readiness Assessment tests</td>
<td>79.80</td>
<td>208.31</td>
<td>17.93</td>
<td>-.405</td>
<td>.433</td>
</tr>
<tr>
<td>Exams</td>
<td>77.0</td>
<td>112.17</td>
<td>16.50</td>
<td>-.300</td>
<td>-.404</td>
</tr>
<tr>
<td>Final Exam</td>
<td>80.00</td>
<td>163.59</td>
<td>20.79</td>
<td>-.592</td>
<td>-.486</td>
</tr>
<tr>
<td>Knowledge Content Test</td>
<td>13.00</td>
<td>17.05</td>
<td>3.11</td>
<td>-.516</td>
<td>-.334</td>
</tr>
</tbody>
</table>
The final structural model, including all paths, allows for direct and indirect effects of the individual factor-attitude toward statistics and the interpersonal factor-experience with group work on statistical performance to be tested. The ecological framework model is displayed in Figure 4-1. The chi-square statistic was statistically significant. However, it should be noted that sample sizes that exceed 200, as in the present study, tend to increase the probability that the chi-square tests will yield statistical significance (Schumacker & Lomax, 1996). The hypothesized model yielded a good fit to the data with the exception of the significance of the chi-square and the NNFI \[\chi^2 = 122.74, df=70, p=0.000; \chi^2/df=1.747; CFI=.959; \text{NNFI}=.947; \text{RMSEA}=.055\] (see Table 4-13).

<table>
<thead>
<tr>
<th>Table 4-13: Fit Indices of Structural Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\chi^2)</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>Original Model</td>
</tr>
<tr>
<td>Modified Model</td>
</tr>
</tbody>
</table>

The ecological theory perspective of statistics performance model fits the data well. However, two paths were not significant: (a) the direct path from individual factor-attitude toward statistics to the degree of active engagement of lab quizzes, and (b) the direct path from the individual factor-attitude toward statistics to the degree of active engagement of group projects (see Figure 4-5). These paths were removed and the
modified hypothesized model was estimated with only statistically significant paths retained, as recommended by Kline (1998) and Lomax (1982).

Figure 4-5: Estimated parameters of the ecological theory perspective statistics performance model

After eliminating the two nonsignificant paths, the revised model also fit the data well with the exception of the chi-square statistic \( \chi^2 = 123.75, df=72, p=0.000; \chi^2/df=1.72; \) CFI=.960; NNFI=.949; RMSEA=.054] (see Table 4-14). The chi-square statistic was statistically significant, which suggests an inadequate fit. However, as noted previously, sample sizes that exceed 200, as in the present study, tend to increase the probability that the chi-square tests will yield statistical significance (Schumacker & Lomax, 1996). These
indices combined suggested that the modified ecological theory perspective of statistics performance model was a good explanation of the data (see Figure 4-6).

Table 4-14 and Figure 4-6 present the results of the parameter estimations. Figure 4-6 shows the parameter estimates of relating variables to their latent construct consisting of the individual factor-attitude toward statistics, the interpersonal factor-experience of group work, and statistics performance. The arrows from a latent factor to its indicator serve as factor loadings, and the arrows from one latent factor to another indicate regression weights.

![Figure 4-6: Final structural model of statistics performance](image)

In Chapter 1, a total of six hypotheses were presented to test each relationship among the five variables in the ecological theory perspective of statistics performance
model. The standardized direct, indirect, and total effects implied by the model are shown in Table 4-14 with corresponding hypotheses. Table 4-14 indicates that the largest effect (.292) on statistics performance was the individual factor-attitude toward statistics with an entire direct effect. Then next most important variables of statistics performance were group projects and lab quizzes with an entirely direct effect of .250 and .203, respectively. The table also shows an unexpected direct negative path from experience with group (-.231) to statistics performance.

Table 4-14: Standardized Causal Effects on Statistics Performance

<table>
<thead>
<tr>
<th>Mediating Variable</th>
<th>Lab Quizzes ($R^2 = .029$)</th>
<th>Projects ($R^2 = .076$)</th>
<th>Statistics Performance ($R^2 = .218$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct Effects</td>
<td>Indirect Effects</td>
<td>Total Effects</td>
</tr>
<tr>
<td>Attitude</td>
<td>.079</td>
<td>-</td>
<td>.079</td>
</tr>
<tr>
<td>Group Experience</td>
<td>.172*</td>
<td>-</td>
<td>.164</td>
</tr>
<tr>
<td>Lab Quizzes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group Projects</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The squared multiple correlations value represents the proportion of variance ($R^2$) that is explained by the predictors of the construct in question (Byrne, 2001). The ecological theory perspective of statistics performance model explained approximately 22 percent of variance of statistics performance.
Summary of Hypotheses Testing

**Hypothesis 1.** The individual factor-attitude toward statistics will have a direct, positive effect on statistics performance.

This hypothesis was supported by the data. There was a significant relationship between the individual factor-attitude toward statistics and statistics performance with a path coefficient of .290. The relationship indicates that the individual factor-attitude toward statistics was significantly and positively related to statistics performance.

**Hypothesis 2.** The interpersonal factor-experience with group work will have a direct, positive effect on statistics performance.

This hypothesis was supported by the data. There was significant and inverse relationship between the interpersonal factor-experience with group work and statistics performance with a path coefficient of -.231. The relationship indicates that the interpersonal factor-experience with group work was significantly and negatively related to statistics performance.

**Hypothesis 3.** The individual factor-attitude toward statistics will have an indirect effect on statistics performance through lab quizzes. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.

This hypothesis was not supported by the data. There was no significant relationship between the individual factor-attitude toward statistics and performance.
through the degree of active engagement of lab quizzes. Thus, the individual factor-attitude toward statistics had no significant or indirect relationship with statistics performance through lab quizzes.

**Hypothesis 4.** The individual factor-attitude toward statistics will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.

This hypothesis was not supported by the data. There was no significant relationship between the individual factor-attitude toward statistics and performance through the degree of active engagement of group projects. Thus, the individual factor-attitude toward statistics had no significant or indirect relationship with statistics performance through the degree of active engagement of group projects.

**Hypothesis 5.** The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of lab quizzes. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.

This hypothesis was supported by the data. There was a significant and positive relationship between the interpersonal factor-experience with group work and performance through the degree of active engagement of lab quizzes with a path
coefficient of .165. In turn, performance through the degree of active engagement of lab quizzes was significantly and positively related to statistics performance with a path coefficient of .203. Thus, the interpersonal factor-experience with group work had a significant and indirect relationship with statistics performance through the degree of active engagement of lab quizzes (indirect effect=.104).

**Hypothesis 6.** The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.

This hypothesis was supported by the data. There was a significant and positive relationship between the interpersonal factor-experience with group work and performance through the degree of active engagement of group projects with a path coefficient .275. In turn, the performance through group projects was significantly and positively related to statistics performance with a path coefficient of .250. Thus, the interpersonal factor-experience with group work had a significant and indirect relationship with statistics performance through the degree of active engagement of group projects (indirect effect=.104).
Summary

This chapter presents the results of assessment of model fit of measurement and structural models for statistics performance based on steps 4 and 5 as described in Chapter 3.

The results from the three confirmatory factor analyses (the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and statistics performance) supported the further use of the measurement model as a part of the ecological theory perspective statistics performance model hypothesizing causal links among latent variables.

The results of the ecological theory perspective of statistics performance model analysis suggested that the modified ecological model was a good explanation of the data, and supported four of six hypotheses in this study. A summary of the results is presented in Table 4-15. This suggests that the statistics performance in the introductory statistics course could be predicted by the relationships among the selected four variables. These results will be discussed in Chapter 5.
Table 4-15: Summary of the Results

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. The individual factor-attitude toward statistics will have a direct, positive effect on statistics performance.</td>
<td>Significant, and positive relationship</td>
</tr>
<tr>
<td>2. The interpersonal factor-experience with group work will have a direct, positive effect on statistics performance.</td>
<td>Significant, not positive (inverse relationship)</td>
</tr>
<tr>
<td>3. The individual factor-attitude toward statistics will have an indirect effect on statistics performance through lab quizzes. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.</td>
<td>Not significant</td>
</tr>
<tr>
<td>4. The individual factor-attitude toward statistics will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the individual factor-attitude toward statistics is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.</td>
<td>Not significant</td>
</tr>
<tr>
<td>5. The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of lab quizzes. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of lab quizzes, the degree of active engagement of lab quizzes will be positively related to statistics performance.</td>
<td>Significant and positive relationship</td>
</tr>
<tr>
<td>6. The interpersonal factor-experience with group work will have an indirect effect on statistics performance through the degree of active engagement of group projects that include peer assessment. If the interpersonal factor-experience with group work is positively related to the degree of active engagement of group projects, the degree of active engagement of group projects will be positively related to statistics performance.</td>
<td>Significant and positive relationship</td>
</tr>
</tbody>
</table>
Chapter 5

DISCUSSION

The main purpose of this study was to conceptualize and empirically test a model intended to predict statistics performance in reformed introductory statistics courses that analyzes the roles of students’ individual factors and interpersonal factors and statistics performance. In the predicted model, there were hypothesized relationships between and among the individual factor-attitude toward statistics and the interpersonal factor-experience with group work that would be mediated by the degree of active engagement in the reformed course activities. That is, the introductory statistics course students exhibiting positive attitude toward statistics or experiences with group work would report higher levels of performance in the degree of active engagement in the reformed course activities, which would, in turn, lead to higher levels of statistics performance.

Ecological theory was adopted as a framework for a comprehensive model of statistics performance in an introductory statistics course. This model hypothesized that the individual factor and the interpersonal factor affect statistics performance directly and indirectly through effects on the degree of active engagement of the reformed course activities.

Data from a total of 249 students enrolled in a 2004 fall semester introductory statistics course were used in this study. Structural Equation Modeling (SEM) was the
data analysis method used to test for model fit, as well as to provide information on statistics performance through analysis of direct, indirect, and total effect. This method consisted of five steps based on the common procedures of analyzing data as recommended by Diamantopoulos and Siguaw (2000).

The results from the confirmatory factor analysis supported the further use of the attitude, experience with group work, and statistics performance measurement model as a part of the ecological theory perspective of statistics performance model, in addition to hypothesizing causal links among latent variables. The ecological theory perspective of statistics performance model analysis suggested that the modified ecological model was a good explanation of the data and supported four of six hypotheses in this study. This suggests that statistics performance in the introductory statistics course could be predicted by the relationships among the selected four variables.

The findings from the ecological theory perspective statistics performance model are discussed by 1) model fit, and 2) direct and indirect effects of each variable. Implications for instructional design and recommendations for future research based on these findings are also discussed.

**Discussion**

Results and discussion in this section address each of the three research questions. Specific research questions that were explored included:

- Does ecological theory explain statistics performance and is the model that is built on this framework consistent with the data?
• Are the identified predictor variables (the individual factor-attitude toward statistics, the interpersonal factor-experience with group work, and the degree of active engagement in the reformed course activities) significant predictors of statistics performance?

• What are the direct, indirect, and total effects of the identified predictor variables on statistics performance?

To answer research question 1, the results for model fit are discussed below, including detailed theoretical rationales for removing the paths that linked attitude toward statistics to the degree of active engagement in the reformed course activities in the modified mode. Then, research questions 2 and 3 are discussed in the light of direct and indirect effects of study variables.

Model Fit

Research question 1 was proposed to examine whether the ecological theory perspective of statistics performance model is consistent with the data.

The confirmatory factor analysis, according to the global model fit indices and the detailed model indicators, shows the initial model was a moderate fit to the data. The results for the model fit indices supported a model revision by allowing the error terms to be correlated. The modified model fit was better on this data set than that for the first model.

The results of the confirmatory factor analysis confirm four factors of the attitude toward statistics latent variable, including affect, cognitive competence, value, and
difficulty. The theoretical model of four latent constructs of attitude toward statistics was tested. With some modifications the model indicated a good fit to the data $[\chi^2 = 642.25, df=343, p=.000; \chi^2/df=1.872; CFI=.96; NFI=.92; RMSEA=.059]$. The results of the confirmatory factor analysis also confirm four factors of the experience of group work latent variable, including confidence, communication, goals, and participation. The theoretical model of four latent constructs of experience with group work was tested. With some modifications the model indicated a good fit to the data $[\chi^2 = 181.04, df=97, p=.000; \chi^2/df=1.86; CFI=.97; NFI=.98; RMSEA=.059]$. The confirmatory factor analysis results confirm four indicators of the statistics performance latent variable, including RATs, mid-term exams, final exam, and knowledge content test. The theoretical model of four indicators of statistics performance was tested. With some modification the model indicated a good fit to the data $[\chi^2 = .346, df=1, p=.556; \chi^2/df=.346; CFI=1.00; NNFI=.99; RMSEA=.000]$. According to the global model fit indices and the detailed model indicators, the initial structural model was a good fit to the data. However, two paths were not significant: (a) the direct path from individual factor-attitude toward statistics to the degree of active engagement of lab quizzes, and (b) the direct path from the individual factor-attitude toward statistics to the degree of active engagement of group projects. The results for the model fit indices were better on this data set than those for the first model, and the detailed fit results supported a model revision by removing these two paths.

After removing the direct paths from attitude toward statistics to the degree of active engagement in reformed course activities in accordance with modification indices,
the modified model fit was improved. The assessment of the global fit indices and the detailed model fit indicators of the modified model indicated that the data seemed to be consistent with the estimated model $\chi^2=123.75$, $df=72$, $p=0.000$; $\chi^2/df=1.72$; CFI=.960; NNFI=.949; RMSEA=.054].

Three confirmatory factor analyses of attitude toward statistics, experience with group work, and statistics performance in the ecological theory perspective of statistics performance model obtained a reasonable fit. The results from the confirmatory factor analysis supported the further use of the measurement model as a part of the ecological theory perspective of statistics performance model hypothesizing causal links among latent variables. The ecological theory perspective of statistics performance model analysis suggested that the modified ecological model was a good explanation of the data. This suggests that statistics performance in the introductory statistics course could be predicted by the relationships among the four selected variables: attitude toward statistics, experience with group work, and degree of active engagement in the reformed courses activities-lab quizzes, and group projects.

Removing the direct paths from attitude toward statistics to degree of active engagement in the reformed courses activities was supported by a study conducted by Wilson (1997). This study revealed that students come to statistics courses with preconceived ideas, opinions, values, and beliefs about their abilities and the course. What students bring to the classroom is more powerful in predicting their anxiety than what instructors can do to prevent it. In the same context, attitude toward statistics is one of the students’ beliefs, and it could be a better direct predictor of statistics performance than the effects of the learning environment created by instructors.
The overall predictive accuracy of the model was not very strong, as the \( R^2 \) was only .22. While this correlation result is not unusual for these types of models (Fenster, 1992), there are other variables that have been determined to influence performance in a course that were not part of the model estimated.

As noted by Lalonde and Gardner (1993), only a paucity of researchers have attempted to model statistics performance using structural equation modeling techniques. Few studies have developed a conceptual model to predict statistics performance. Three studies that have been proposed were adopted from the areas of second language learning (Lalonde & Gardner, 1993; Onwuegbuzie, 2003; Tremblay et al., 2000) and student persistence and achievement goal theory (Bandalos et al., 2003).

Although there have been many studies of statistics performance, few have dealt with mediating effects of active engagement in reformed course activities in higher education. Therefore, development of the study model and the empirical results that were generated extend the understanding of adoption and utilization processes of reformed introductory statistics course activities in higher education.

However, this result may appear to contradict the negative significant effect of interpersonal factor-experience with group work on statistics performance. One reason this result might have emerged is due to the time when the survey was given to the students. The experience with group work predicted the degree of active engagement in the reformed course activities in this study model; however, the data about the experience with group work were collected at the end of the semester. The result might be different when the experience with group work survey is given to students at the beginning of the semester.
Therefore, an alternative model was developed to solve the inverse relationship of the model. In this alternative model, the directions of two direct paths have been changed in the consideration of the time of the survey utilization: (a) the direct path from the degree of active engagement of lab quizzes to the interpersonal factor-experience with group work, and (b) the direct path from the degree of active engagement of group projects to the interpersonal factor-experience with group work. The assessment of the global fit indices and the detailed model fit indicators of the alternative model indicated that the data seemed to be consistent with the estimated model $[\chi^2 = 123.75, df=72, p=0.00; \chi^2/df=1.72; CFI=.960; NNFI=.950; RMSEA=.054]$ (See Figure 5-1). The global fit indices were the same as the original structural model of statistics performance; however, the path coefficients of these two paths slightly decreased. Another alternative model also was tested in which the directions of the direct path were changed from statistics performance to the interpersonal factor-experience with group work, and this provided similar results.
The study found that the more negative the students’ experience with group work, the higher their scores on statistics performance. Whether the students’ negative experience with group work can be attributed to their success in their statistics course, or vice versa, cannot be answered because these data were collected only after students completed the statistics course. The experience with group work scale scores for those who had not had group work in their previous courses hint that the first supposition is reasonable; those who had not experienced group work in previous courses had less favorable, but different, experience with group work than those who had experienced group work in previous courses.

Figure 5-1: Alternative structural model of statistics Performance
Direct and Indirect Effect of Each Variable

Research question 2 asked whether the four identified predictor variables—attitude toward statistics, experience with group work, degree of active engagement of lab quizzes, and group projects—were significant for predicting statistics performance. Research question 3 asked: Assuming those variables were significant, then what were the direct, indirect, and total effects of the identified predictor variables on statistics performance?

The Individual Factor-Attitude toward Statistics

The results showed that attitude toward statistics predicts statistics performance directly (H1), but not indirectly (H3 and H4). If one had a positive attitude toward statistics, one was more likely to perform well in the introductory statistics course.

The result that attitude toward the statistics is related positively to performance on statistics is consistent with the literature (Ellman, 1991; Elmore et al., 1993; Green, 1994; Kottke, 2000; Scott, 2002; Townsend et al., 1998; Wise, 1985). Indeed, this finding is consistent with researchers who have found that attitude toward statistics predicts effective study of introductory statistics (Gal & Ginsburg, 1994). Relations within the perspective of ecological theory statistics performance model indicated attitude toward statistics had the most influence on statistics performance.

Although this study revealed a significant positive relationship between attitude toward statistics and statistics performance, the strength of this relationship was not as
strong as has been reported in other studies (Kottke, 2000; Scott, 2002; Townsend et al., 1998).

The lack of indirect influence of attitude toward statistics on the degree of active engagement in the reformed course activities in this model was surprising. In a constructivistic learning environment, learning is affected by the context and the attitudes of learners. Students’ attitudes and expectations may mediate with aspects of the learning environment created by instructors. This result may suggest that what students bring to the classroom is a more powerful predictor of performance than what instructors could do with the active engagement in course activities.

The findings did not support research about indirect effects of attitude toward statistics on statistics performance. As mentioned in the previous chapter, in the reality of higher education it is expected that one variable may indirectly affect another through one or more intervening variables. However, the indirect effect was not significant in this study.

Considering the changes in statistics learning and instruction, questions related to student attitudes are of interest, because student attitude about statistics may influence the learning process. Research on students’ attitude towards statistics has led to a need for research about the role played by emotional information in memory and in the environment (Loftus, 1990).

In particular, students’ attitudes and beliefs about statistics can affect the extent to which students will develop useful statistical thinking skills, whether they will apply what they have learned outside of the classroom, and whether or not students will choose to enroll in further statistics courses (Gal et al., 1997).
The Interpersonal Factor-Experience with Group Work

Experience with group work was included in this study in order to capture interpersonal effects. Experience with group work was found to be predictive of statistics performance directly (H2), and indirectly (H5, H6). There was a significant and positive indirect relationship between the interpersonal factor-experience with group work and statistics performance. However, an unexpected result in this study was the negative effect of the experience of group work on statistics performance. This result showed that if one had negative experience with group work, one was more likely to perform better in the introductory statistics course.

This was unexpected in that prior research indicated a positive relationship between collaborative learning and performance, as well as between the perceptions of collaborative learning and performance. Thus, there are conflicting findings related to the influence of the experience of group work on statistics performance. The negative reactions to group learning experience found in this study were consistent with the study by Colback, Campbell, and Bjorklund (2000).

However, the findings of previous research supported the direct positive effects found concerning experience of group work on statistics performance (Giraud, 1997; Peterson & Miller, 2004; Potthast, 1999; Slavin, 1990; Wood, 1987).

There are at least two plausible reasons why these unexpected findings occurred. First, in most situations, faculty members assign projects with single group goals and rewards for all members of each team. Slavin (1989) argued that group rewards or grades based on a single group product may set up conditions where one or two members do most of the work.
Many students have already developed insights about how to work collaboratively from previous positive group experiences. Students have experienced that someone else can spark an idea or do most of work in order for their team to keep its planned schedule. This may mean that they will not work or study as they are supposed to, so their individual performance is not improved.

In another case, many students wanted to avoid being grouped with “slackers,” those who had done minimal work on previous projects. Many students who worried about “slackers” used avoidance as the common strategy for dealing with them. However, students’ comments from Colbeck’s study revealed a variety of attitudes and strategies for dealing with slackers. The most common strategy they could use was, if possible, to let slackers leave the group (Colbeck et al., 2000). Because of these types of negative experiences individual students felt forced to prepare finish or submit the project. Therefore, we may conclude that the remaining group members had a negative experience with group work, but achieved high performance of achievement on their individual performance.

In another study, Jehn (1997) conducted research about the conflicts within groups and showed that conflicts over personal issues can have negative effects on group productivity and members’ satisfaction. When group members had negative experiences—such as when they perceived that other members were not taking the task seriously, or were sharing ideas that were not helpful, or were not giving much help on improving the project— they tried to convince the other group members that their own ideas should be considered or adopted. These ideas were offered in an attempt to correct
or improve the project. These conflicts help students to prepare well and direct them to study.

This result can be explained through a study by Bosworth and Hamilton (1994), in which it was found that students are more likely to attain positive outcomes from group experiences when the instructor provides information and guidance about how to work together. Students were particularly frustrated when they believed the instructor had poor group guidance skills or shirked responsibility for helping the groups (Fiechtner & Davis, 1984-85). These results are also supported by those summarized by John and John (1994) and Slavin (1988), who reviewed the collaborative learning literature. Both studies suggested that instructors should provide very specific guidance.

This might explain the results of the present study because the instructor only helped groups who asked a question or asked for help for their group work, rather than providing help to all groups or all students. Some students might have been too shy to ask a question.

The results of this study show that perceptions of experience with group work do appear to have serious consequences in terms of statistics performance.

The Reformed Introductory Statistics Course Activities

Study results indicate that the degree of active engagement in the reformed course’s activities, lab quizzes, and group projects with peer assessment, mediate between the experience with group work and statistics performance. Specifically, experience with group work has an indirect effect on statistics performance through its
impact on the reformed introductory statistics activities. Since the negative direct effect was found, the significant indirect effect is more critical for the instructor and the instructional designer. As mentioned previously, in the reality of higher education it is expected that one variable may indirectly affect another through one or more intervening variables. The indirect effects were significant in this study.

A particularly interesting finding is the fact that, whereas the indirect path from attitude toward statistics to statistics performance was not significant, and the direct path from experience with group to statistics performance was negative, on the other hand the indirect paths from experience with group work to statistics performance were significant and positive. This is the most important finding: that the reformed course activities helped and led to a more positive significant effect on statistics performance, and might mitigate the negative direct effect.

The present results suggest that interventions designed at reducing the level of students’ negative perception of experience with group work, as well as improving their attitude toward statistics may have a direct positive effect on statistics performance.

The current study contributes to the general understanding of statistics performance, which may be of interest to theorists and statistics instructors as they design their courses. Examination of relationships among attitudes toward statistics, experience of group work, and the reformed statistics course activities and statistics performance can also enhance the ecology perspective model of ecology development systems theories.
Implications for Instructional Design

One of the practical implications of the present results has to do with intervention activities for students who are experiencing difficulties in statistics. A variety of interventions can help students enrolled in an introductory statistics course: increasing positive attitude toward statistics, reducing the negative perceptions of experience with group work, or the combination of these strategies. This result of the study suggests that focusing on the degree of active engagement in reformed course activities may be just as effective as focusing on other interventions, given the indirect impact that experience with group work can have on statistics performance.

When it comes to teaching, it is beneficial to view statistics education through an ecology development theory framework. We can borrow certain teaching strategies and theories that have been found to be effective with ecology development theory.

The conditions for group learning in a higher education setting rarely meet the standards advocated by scholars of cooperative learning. In this study, the results of the experience with group work suggested that it may be necessary for the instructor to provide specific and clear guidance in order to foster a positive experience with group work. Few faculty members have formal training about how to manage group dynamics. It is important to develop resources or workshops about how to manage groups as instructional design support for faculty members.

The present results suggest that interventions designed at improving attitude toward statistics, as well as students’ experience with group work, may have a total direct effect on statistics performance. The results of this study would also be helpful to instructional designers. When it comes to successful educational program design, the
considerations of the target audience’s characteristics are essential to the analysis phases in most instructional design models.

The results of this study may have application to other types of instruction in higher education that are implementing innovations. Without models that contain relevant and valid factors, adoption and implementation of innovations cannot be easily explained, predicted, or improved.

**Recommendations for Future Research**

The present study shows the usefulness of model generation and model testing in the area of statistics performance. This study also shows the contextual influences on students’ statistics performance by reflecting the interrelationships among students and the contexts. Many students find it difficult to grasp statistical concepts and therefore attain lower levels of performance on statistics than they do on other examinations taken in the course of obtaining their degree (Onwuegbuzie & Seaman, 1995).

Yet the model has a substantial amount of unexplained variance for the targeted variables at the end of the course, indicating that the inclusion of additional variables could possibly provide improvement of the model. It is likely that some important variables were omitted from the preliminary model. For example, gender differences and anxiety in statistics performance have been documented. It would be beneficial to investigate the influence of other individual factors and the interpersonal factors, in order to reach a more complete understanding of the ecology theory perspective of
statistics performance model. It is strongly recommended that additional validation of the constructs be made in a future study.

Although there have been many studies about statistics performance, few have dealt with the relationships among the factors of attitude toward statistics, and experience with group work including mediating effects of active engagement in a reformed course’s activities in higher education. Therefore, another important area of study is the development of a study model and application of the generated empirical results to the understanding of statistics performance in higher education.

A theoretically grounded and well-researched approach in education that can increase students’ learning of subject matter and improve their attitudes toward both academics in general and the subject matter specifically is needed (Springer et al., 1999). It is important for researchers to continue to explore this relationship.

Many statistics educators have discussed the perceived negative attitudes of statistics students. The general results of these models supported the theoretical predictions. However, the relationship between negative attitudes and statistics performance with the interventions merits further consideration. Also, understanding how students experience various instructional activities is important because their experiences will influence not only what they learn in their academic subjects but also what they learn about the value of collaboration.

There are some limitations in this study which should be considered in terms of the generalizability of the present findings and in terms of future research. This study provides a preliminary test of a model that needs further testing with different samples in order to test its replicability across samples and gender. Other researchers may want
to hypothesize alternative models having different patterns of relations among the variables and compare the adequacy of those models to the one examined in this study.

Conclusions

A significant, positive direct effect was found between the individual factor-attitude toward statistics and statistics performance. A significant, positive indirect effect was also found between the interpersonal factor-experience with group work on statistics performance through lab quizzes and group projects.

However, there were no significant indirect effects between the individual factor-attitude toward statistics and the degree of active engagement in the reformed course activities-lab quizzes and group projects. There was significant, negative direct effect between the interpersonal factor-experience with group work and statistics performance.

In conclusion, it is likely that higher education institutions will continue to encourage college and university students to take introductory statistics courses as a degree requirement for graduation. The findings in this study provide a basis for consideration when reformed course activities, such as readiness assessment, lab quizzes incorporating technology, and collaborative learning with peer assessment are introduced and implemented in statistics courses. The findings of this study not only confirmed the findings of most statistics performance studies, which use a single equation model like the regression model that represents only direct effects of determinants on an outcome, but also provided indirect effects of determinants on an outcome. These indirect effects, when added to the direct effects in the model, allow the
determination of total causal effects of determinants on an outcome variable. Therefore, development of the study model and the empirical results generated in this study add to the understanding of statistics performance in the reformed introductory statistics course in higher education. This study also contributes to the research by initiating the validation of a theoretical framework of ecology development model. The framework and the results of the present study may stimulate future research and practice in statistics education.
References


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National Council for the Accreditation of Teacher Education. (2000). *Standards, procedures, and policies for the accreditation of professional education units*. Washington, DC.


APPENDIX A

HUMAN PARTICIPANTS’ SECONDARY DATA APPROVAL LETTER
Date: August 29, 2005

From: Tracie L. Kahler, IRB Administrator

To: Heeyoung Kim

Subject: Results of Review of Proposal – Expedited (IRB #21436) Secondary Data Approval Expiration Date: August 14, 2006
"A Model for Predicting Performance in Introductory Statistics Course"

The Social Science Institutional Review Board (IRB) has reviewed and approved your proposal for use of human participants in your research. By accepting this decision, you agree to notify the Office for Research Protections (ORP) of any additions or changes in your study procedures that would alter participant risk.

If this study will extend beyond the above noted approval expiration date, it is the principal investigator’s responsibility to submit a completed Continuing Progress Report to the ORP to continue approval of this research.

On behalf of the IRB and the University, thank you for your efforts to conduct your research in compliance with the federal regulations that have been established for the protection of human participants.

TLK/mhc
cc: Barbara L. Grabowski

Please Note: The ORP encourages you to subscribe to the ORP listserv for protocol and research-related information. Send a blank email to L-ORP-Research-L-subscribe-request@lists.psu.edu
APPENDIX B

STUDENTS GENERATED DATASET SURVEY
Students Generated Dataset Survey

As a class activity, data obtained on students in the class, including

- gender
- age
- physical measurements
  - height and ideal height
  - weight and ideal weight
  - length of left and right forearms
  - length of left and right foot
  - width of the left and right hand
  - span from little finger to end of thumb on left and right hands
  - two measurements of head circumference
  - distance around chest
  - length of left and right arm
  - waist
- longer finger: ring or index
- handedness: left or right
- race
- hair color
- eye color
- eye color most attracted to (or by)
- feature in another person most attracted to
- view of one’s weight
- number of days per month one has at least 2 beers
- number of parties one goes to per month
- number of times per week one exercises
- gpa
- credit load
- number of hours one studies per week
- The academic year
- Race
- In a typical week, about how many minutes do you think you spend talking on a cell phone?
- What is the fastest speed you have ever driven?
- What is your actual height?
APPENDIX C

GROUP PROJECTS ASSIGNMENT
Group Projects Assignment

Project 1

As a class activity, data were obtained on students in the class, including
gender (C1)
age (C2)
physical measurements
  height (C3) and ideal height (C4)
  weight (C5) and ideal weight (C6)
  length of left (C7) and right (C8) forearms
  length of left (C9) and right (C10) foot
  width of the left (C11) and right (C12) hand
  span from little finger to end of thumb on left (C13) and right (C14) hands
  two measurements of head circumference (C15 and C16)
  distance around chest (C17)
  length of left (C18) and right (C19) arm
  waist (C20)
  longer finger: ring or index (C21)
handedness: left or right (C22)
race (C23)
hair color (C24)
eye color (C25)
eye color most attracted to (or by) (C26)
feature in another person most attracted to (C27)
view of one’s weight (C28)
number of days per month one has at least 2 beers (C29)
number of parties one goes to per month (C30)
number of times per week one exercises (C31)
gpa (C32)
credit load (C33)
number of hours one studies per week (C34) The results are contained in the
dataset “Student Characteristics”.

Data on these variables is stored in a dataset named ‘Physical Data’. It is a Minitab
Worksheet ready for you to use.

1. We know that males and females differ in bodily characteristics. Describe some of
these differences using three or four physical measurements. You should obtain
descriptive statistics and at least one graphical display, put them in your report, and
interpret them [comment on the means (or medians) and variability (standard
deviations or interquartile range)] of these variables. For example, you might say
‘the average height of males is about 5’ more than females, but heights of females
are more variable than males (if this is true of course!). Give the five-number
summaries for one of the physical measurement variables by gender. Document your statements by referring to the descriptive statistics.

2. Using the variables you used in (A), make similar comparisons by race. Are the differences practically significant (that is, do they appear to be worth mentioning)? Write a brief paragraph summarizing your results. Document your statements by referring to the descriptive statistics and graphical displays... Check for outliers and decide what to do with them (leave them in? throw them out because the values are obviously wrong?)

3. Identify a physical measurement which has a bell-shaped distribution and include a graphical display which shows this. Then use the ‘Empirical Rule’ to find the intervals which should contain 68%, 95%, and almost all of the measurements for this variable.

Guidelines for the Project:

1. Write an introductory paragraph listing the variables you chose and explaining why you chose them (there is no ‘right’ answer—reader’s of your project should know why you decided to use these variables). Also, before you do the statistical analyses create research questions for each physical variable about the comparisons you will be making. For example, you might say “We know males are taller than females on the average, but we would like to know how much taller”. Do this for comparisons by gender and by race.

2. Write a paragraph summarizing your results for both gender and race.

3. Prepare your report, including the following:
   - A title page, containing the names of your group members and your group number.
   - The introductory paragraph (item 1 above), with group number at the top of the page, but no other identification of group members.
   - Content by gender (Part A, as described above)
   - Content by race (Part B, as described above)
   - Part C, as described above.
   - Summary paragraph (item 2 above).
   - Submit your report by putting it in the drop box provided in ANGEL.

4. A scoring rubric will be handed out later. You will first prepare a draft of your report, which will then be sent to 4 other students for them to critique. Their critiques will then be given to you for use in any possible revisions you wish to make. A ‘timetable’ for the various aspects of this project will also be given to you.
5. I assume you will be using Microsoft Word for this project. When you do the Minitab portion of the project, be sure to save your work. Output in Minitab can be copied and pasted into MS Word and edited. To save graphical displays, put cursor on the ‘graphic/object’, go to Edit, and click Copy. Then go to MS Word and paste it in. You can ‘resize’ and move objects in Word as follows: a. click on the object; b. click Format>Object/Layout. c. click ‘Advanced’ and choose one of the ‘squares’ you wish to use (no wrapping, one side etc.)

Group Project 2

Submit a typed group report with a cover page that indicates each member’s name, group number, and a signature for each member. The signature is testimony that the person actually participated.

1. Problem 1. (20 Points) Go to the FAQ section of the Gallup Poll web site and read the article entitled: “How polls are conducted. The web site link is in Angel (see Important Links). Based on the article there, answer the questions below.
   a. About what aspect (or aspects) of the Gallup Poll are Americans most skeptical?
   b. What is the sampling frame that is typically used by Gallup? Be specific
   c. What does the Gallup Poll do to minimize the possibility of a non-response bias?
   d. Some households have more than one adult who would be in Gallup’s sampling frame. How does Gallup randomly sample from these households?
   e. Explain the “split sample technique” that has been used by Gallup over the years.

2. Problem 2. (10 Points) Stephen J. Gould, a biologist, studied how one could compare performances of various kinds across past years. Here is one example. Three landmarks of baseball achievement are Ty Cobb’s batting average of .420 in 1911, Ted Williams’s .406 in 1941, and George Brett’s .390 in 1980. These batting averages can’t be compared directly because the distribution of major league batting averages has changed over the decades. The distributions are quite symmetric and (except for outliers such as Cobb, Williams, and Brett) reasonably normal. Here are some facts about batting averages:

<table>
<thead>
<tr>
<th>Decade</th>
<th>Mean Batting Average</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1910’s</td>
<td>.266</td>
<td>.0371</td>
</tr>
<tr>
<td>1940’s</td>
<td>.267</td>
<td>.0326</td>
</tr>
<tr>
<td>1970’s</td>
<td>.261</td>
<td>.0317</td>
</tr>
</tbody>
</table>
a. Comment on the ‘Mean Batting Average’ (are they about the same, decreasing, increasing etc.)

b. Comment on the ‘Standard Deviations’ (are they about the same, decreasing, increasing etc.)

c. Interpret what the behavior of the standard deviations says about the spread (variation) in batting averages over the three decades.

d. One way to compare the performance of the three baseball achievements is to standardize (using z-scores) their values (batting averages). Do this and then comment on which player seems to have had the greatest performance. Draw a curve to illustrate and justify what you say.

3. Problem 3. (20 Points) A researcher wants to see if the regular use of Vitamin C reduces the risk of getting a cold.

   a. What are the response and explanatory variables?
   b. Briefly describe how the researcher could do an observational study to examine this relationship.
   c. Suppose that 100 people are available for an experiment. Describe a randomized experiment for this problem.
   d. Why would it be better to do an experiment rather than an observational study to examine this relationship?
   e. Briefly explain the term “double-blind” as it applies to randomized experiments

4. Problem 4. (20 Points) The faculty senate at a large university wanted to know what proportion of the students think a foreign language should be required of everyone. The statistics department offered to cooperate in conducting a survey, and a simple random sample of 500 students was selected from all students enrolled in statistics classes. A survey form was sent by email to these 500 students.

   a. What is the population of interest to the faculty senate?
   b. What is the parameter of interest?
   c. Is the sample representative of the population of interest? Explain.
   d. Describe an alternative sampling method for obtaining a sample to estimate the parameter of interest.
   e. The faculty senate believes that the proportion of students who think a foreign language should be required of everyone varies by the college they are enrolled in (for example, business, liberal arts, engineering, etc.). Describe a sampling scheme which will enable them to estimate the proportion for each college.

5. Problem 5 (30 Points) "Old Faithful Geyser in Yellowstone National Park, Wyoming, derives its name and its considerable fame from the regularity (and beauty) of its eruptions. As they do with most geysers in the park, rangers post the predicted times of eruptions on signs nearby, and people gather beforehand to witness the show. A park geologist collected 107 measurements on the
durations \((x_1, \text{ in minutes})\) of Old Faithful eruptions, ambient temperature \((x_2, \text{ in Fahrenheit})\) at the time of eruption, height \((x_3, \text{ in feet})\) of the eruption, and intervals \((y, \text{ in minutes})\) until subsequent eruption. For example, in the first observation the duration of the eruption preceding the next eruption was 4.4 minutes and the interval (time) from this eruption to the next eruption was 78 minutes. The data is stored in the file named 'Old Faithful'.

6. You are called in as a statistician to examine "Old Faithful" and to prepare an article reporting on it reflecting what you know as a ‘statistician’. Assess the strength of the relationships between the predictors \(x_1, x_2, \text{ and } x_3\), with \(y\) and determine which of the variables does the best job of predicting the time \(y\) between eruptions. The park ranger posts predicted times of eruptions on signs—Explain how the ranger is able to make predictions. Illustrate this for the case when an eruption lasts 4 minutes. Give a measure of how well the interval between eruptions can be predicted using the best predictor and show how it is calculated. Obtain ‘prediction intervals’ for the time between eruptions and then discuss how they could be used to enhance the safety of visitors who wish to view eruptions.

Some Minitab Commands for Correlation and Regression:
Correlations: Stat>Basic Statistics>Correlation
Regression Equation and Optional Output: Stat>Regression>Regression.
Options: Prediction Intervals for New Observations (select the ‘predictor’)
Storage: Select ‘Fits’: This will result in ‘Prediction Intervals and fitted values being stored in the Minitab worksheet—look at this output!)

Scatter Plot with Fitted Regression Line: Stat>Regression>Fitted Line Plot
Peer Assessment Guideline

Group Problem Solving and Peer Assessment guideline

1. Form a group
2. Working as a group
3. Instructor provides the checklists for group projects
4. Submit written report as a group
5. Instructor assigns three group projects for each group anonymously
6. Assess another group’s projects with peer assessment checklists
7. Review the feedback from peer assessment
8. Revise the report on basis of peer assessment
9. Resubmit the report
10. Instructor or TA grades the final version of the group report.

Peer Assessment Checklists for Group Problem Solving

Problem 1. (20 Points) FAQ section of the Gallup Poll

a. About what aspect (or aspects) of the Gallup Poll are Americans most skeptical?
   - 4 : answer appropriately and adequately.
   - 3 : answer part of the aspect(s)
   - 2 : get the idea but it is badly stated.
   - 1 : answer something but not a useful answer
   - 0 : not answered.

b. What is the sampling frame that is typically used by Gallup? Be specific.
   - 4 : give a definition of the sampling frame and specify how Gallup has been used.
   - 3 : give a definition of the sampling frame, but fail to specify how Gallup has been used but say something about U.S. population
   - 2 : give a definition of the sampling frame, but fail to specify how Gallup has been used .
   - 1 : not mentioned a definitions of the sampling frame, but say something about U.S. population
   - 0 : not mentioned.

c. What does the Gallup Poll do to minimize the possibility of a non-response bias?
   - 4 : identify all aspects of minimizing the possibility of a non-response bias adequately.
   - 3 : identify some of it.
   - 2 : identify something but it is not specific.
   - 1 : rambling non-specific answer
   - 0 : not answered.
d. Some households have more than one adult who would be in Gallup’s sampling frame. How does Gallup randomly sample from these households?
   - 4: describe all possible processes of random sampling.
   - 3: describe some of it.
   - 2: describe something but it is not specific.
   - 1: rambling non-specific answer
   - 0: not answered.

e. Explain the “split sample technique” that has been used by Gallup over the years.
   - 4: explain correctly how Gallup has used the split sample technique.
   - 3: explain some of it.
   - 2: explain something but it is not specific.
   - 1: rambling non-specific answer
   - 0: not answered.

**Problem 2. (10 Points) Baseball Batting average**

a. Comment on the ‘Mean Batting Average’
   - 2: comment on the mean batting average appropriately.
   - 1: comment but it is incorrect.
   - 0: not answered.

b. Comment on the ‘Standard Deviations’
   - 2: comment on the standard deviation appropriately.
   - 1: comment but it is incorrect.
   - 0: not answered.

c. Interpret what the behavior of the standard deviations says about the spread (variation) in batting averages over the three decades.
   - 3: interpret the behavior of the standard deviations appropriately.
   - 2: interpret something but it is not specific.
   - 1: rambling non-specific answer.
   - 0: not answered.

d. One way to compare the performance of the three baseball achievements is to standardize (using z-scores) their values (batting averages). Do this and then comment on which player seems to have had the greatest performance. Draw a curve to illustrate and justify what you say.
   - 4: specify all z-scores of batting averages, and identify the greatest performance with a curve correctly.
   - 3: specify part of the required information
   - 2: specify part of the required information but it is incorrect.
   - 1: rambling non-specific answer.
Problem 3. (20 Points) Use of Vitamin C

a. What are the response and explanatory variables?
   - 4: specify both explanatory variable and response variable correctly.
   - 3: specify either explanatory variable or response variable correctly.
   - 2: specify both variables, but it is incorrect.
   - 1: specify either one of variables, but it is incorrect.
   - 0: not answered

b. Briefly describe how the researcher could do an observational study to examine this relationship.
   - 5: describe an observational study to examine this relationship appropriately.
   - 4: describe an observational study to examine this relationship but fail to use given problem.
   - 3: describe an observational study to examine this relationship, but it is unclear.
   - 2: describe the idea but it is badly stated.
   - 1: describe something but not a useful answer
   - 0: not answered

c. Suppose that 100 people are available for an experiment. Describe a randomized experiment for this problem.
   - 5: describe a randomized experiment appropriately.
   - 4: describe a randomized experiment but fail to use given problem.
   - 3: describe a randomized experiment, but it is unclear.
   - 2: describe the idea but it is badly stated.
   - 1: describe something but not a useful answer
   - 0: not answered

d. Why would it be better to do an experiment rather than an observational study to examine this relationship?
   - 3: describe the correct reason of doing an experiment.
   - 2: describe something but it is not specific.
   - 1: rambling non-specific answer.
   - 0: omitted answer.

e. Briefly explain the term “double-blind” as it applies to randomized experiments
   - 3: explain the definition of double-blind well
   - 2: explain something but it is not specific.
   - 1: rambling non-specific answer.
Problem 4. (20 Points) Foreign Language Requirement

a. What is the population of interest to the faculty senate?
   - 3 : identify the population of interest appropriately.
   - 2 : identify the idea but it is badly stated.
   - 1 : identify something but it is incorrect
   - 0 : not answered.

b. What is the parameter of interest?
   - 3 : identify the parameter of interest appropriately.
   - 2 : describe the idea but it is badly stated.
   - 1 : describe something but it is incorrect
   - 0 : not answered.

c. Is the sample representative of the population of interest? Explain.
   - 4 : answer appropriately and adequately.
   - 3 : answer part of the aspect(s)
   - 2 : sort of get the idea but it is badly stated.
   - 1 : say something but not a useful answer
   - 0 : not answered.

d. Describe an alternative sampling method for obtaining a sample to estimate the parameter of interest.
   - 5 : describe an alternative sampling method appropriately.
   - 3 : describe an alternative sampling, but it is unclear.
   - 2 : sort of get the idea but it is badly stated.
   - 1 : say something but not a useful answer
   - 0 : not answered

e. The faculty senate believes that the proportion of students who think a foreign language should be required of everyone varies by the college they are enrolled in (for example, business, liberal arts, engineering, etc.). Describe a sampling scheme which will enable them to estimate the proportion for each college.
   - 5 : describe a sampling scheme appropriately.
   - 3 : describe a sampling scheme, but it is unclear.
   - 2 : sort of get the idea but it is badly stated.
   - 1 : say something but not a useful answer
   - 0 : not answered

Problem 5 (30 Points) Old Faithful Geyser
a. Assess the strength of the relationships between predictors with y
   • Yes/no

b. Determine which of the variables is the best predictor and why
   • Yes/no

c. Explain how the ranger is able to make predictions
   • Yes/no

d. Illustrate this for the case when an eruption lasts 4 minutes
   • Yes/no

e. Measure of how well the interval between eruptions can be predicted using the best predictor and show how it is calculated
   • Yes/no

f. Obtain ‘prediction intervals’ for the time between eruptions and discuss how they could be used to enhance the safety of visitors who wish to view eruptions
   • Yes/no
APPENDIX E

SURVEY OF ATTITUDE TOWARD STATISTICS (SATS)
Survey of Attitude Toward Statistics (SATS)

DIRECTIONS: The questions below are designed to identify your attitudes about statistics. The item scale has 7 possible responses; the responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). Please read each question. From the 7-point scale, carefully mark the one response that most clearly represents your agreement with that statement. Use the entire 7-point scale to indicate your degree of agreement or disagreement with our items. Try not to think too deeply about each response. Record your answer and move quickly to the next item.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Strongly Disagree</th>
<th>Neither disagree nor agree</th>
<th>Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I will like statistics.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>I will feel insecure when I have to do statistics problems.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>I will have trouble understanding statistics because of how I think.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>Statistics formulas are easy to understand.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>Statistics is worthless.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>Statistics is a complicated subject.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>Statistics should be a required part of my professional training.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>Statistical skills will make me more employable.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>I will have no idea of what's going on in statistics.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>Statistics is not useful to the typical professional.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>11</td>
<td>I will get frustrated going over statistics tests in class.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>Statistical thinking is not applicable in my life outside my job.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>I use statistics in my everyday life.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>14</td>
<td>I will be under stress during statistics class.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>15</td>
<td>I will enjoy taking statistics courses.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>16</td>
<td>Statistics conclusions are rarely presented in everyday life.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>17</td>
<td>Statistics is a subject quickly learned by most people.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>18</td>
<td>Learning statistics requires a great deal of discipline.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>19</td>
<td>I will have no application for statistics in my profession.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>20</td>
<td>I will make a lot of math errors in statistics.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>21</td>
<td>I am scared by statistics.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>22</td>
<td>Statistics involves massive computations.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
23. I can learn statistics. 1 2 3 4 5 6 7
24. I will understand statistics equations. 1 2 3 4 5 6 7
25. Statistics is irrelevant in my life. 1 2 3 4 5 6 7
26. Statistics is highly technical. 1 2 3 4 5 6 7
27. I will find it difficult to understand statistics concepts. 1 2 3 4 5 6 7
28. Most people have to learn a new way of thinking to do statistics. 1 2 3 4 5 6 7

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

29. How well did you do in your high school mathematics courses?

<table>
<thead>
<tr>
<th>Very poorly</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

30. How good at mathematics are you?

<table>
<thead>
<tr>
<th>Very poor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

31. How much computer experience have you had?

<table>
<thead>
<tr>
<th>None</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

32. How much experience with statistics have you had (e.g., courses, research studies)?

<table>
<thead>
<tr>
<th>None</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

33. In the field in which you hope to be employed when you finish school, how much will you use statistics?

<table>
<thead>
<tr>
<th>Not at all</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

34. How confident are you that you can master introductory statistics material?

<table>
<thead>
<tr>
<th>Not at all confident</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
</table>

35. In general, how do you compare females' and males' skills in statistics?
Females much better | Females and males about the same | Males much better
---|---|---
1 | 2 | 3 | 4 | 5 | 6 | 7

DEMOGRAPHIC INFORMATION: Notice that the response scale changes on each item.

36. Your sex:
   1. Male 2. Female

37. Your ethnicity:
   1. White American
   2. Native American
   3. African American
   4. Hispanic American
   5. Asian American
   6. Other American
   7. Foreign Student

38. Degree you are currently seeking:
   1. Associate
   2. Bachelors
   3. Masters
   4. Doctorate
   5. Certification
   6. Post-bachelor's Licensure
   7. Specialist
   8. Other

ADDITIONAL INFORMATION --

Directions: Please fill in the following information about yourself.

1. The last five digits of your student identification
2. Number:______________________
3. Your birth date: _____ and birth year: ______.
4. Number of credit hours earned toward the degree you currently are seeking (don't count this semester); estimate if you don't know:________
5. Current grade point average:________
6. Number of years of high school mathematics taken:________
7. Number of college statistics courses taken:______
APPENDIX F

THE SURVEY OF EXPERIENCE WITH GROUP WORK
The Survey of Experience with Group work

Direction: The questions below are designed to identify your perceptions of how the group work experience has affected your learning. The item scale has 5 possible responses; the responses range from 1 (strongly disagree), 3 (Neutral) to 5 (Strongly agree). Please read each question. From the 5-point scale, carefully mark the one response how you feel most of the time. Try not to think too deeply about each response. Record your answer and move quickly to the next item.

<table>
<thead>
<tr>
<th>Question</th>
<th>Strongly disagree</th>
<th>Neutral</th>
<th>Strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I felt that I learned better when students taught each other rather than having instructors.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2. I preferred learning in groups with other students to learning from lectures.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3. I learned best when I was required to work collaboratively with other students on course assignments.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>4. I learned a great deal when I studied in groups outside of class.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>5. All group members shared their ideas freely.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>6. My group members offered support and encouragement to each other.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>7. My group members asked each other questions to make sure everyone understood the ideas and information we were working with.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>8. My group was energetic. We welcomed new ideas, showed enthusiasm, and laughed with each other.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>9. It was always easy to know the goals of group projects expected.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>10. My group members usually had a clear idea of where we were going and what was expected of us in group projects.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>11. It was not often hard to discover what was expected of us in group projects.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>12. The faculty made it clear right from the start what was expected of students.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>13. My group members have attended the group meeting scheduled during the class time.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>14. My group members made an effort at assigned projects.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>15. My group members attempted to make contributions and/or seek help within the group when we need it.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>16. My group members cooperated with group effort.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
Knowledge Content Test

The purpose of this test is to obtain information on what students know about statistics prior to taking this course. You may know how to answer some of the questions because you had a course in statistics in high school or elsewhere prior to signing up for this course. There are some questions that you may not have any idea what the answers are—in this case, you need not give an answer: skip to the next question. Otherwise, choose that (one correct) answer that seems best to you.

1. Five students were asked how many credits they are taking this semester. The results were as follows:
   18  15  17  12  16.

   The median number of credits taken is
   a.  12  b.  15  c.  16  d.  17

2. A student said his SAT Math score was at the 90th percentile. This means that
   a. the student got 90% of the questions wrong
   b. the student got 90% of the questions right
   c. 90% of students had a lower score than the student
   d. 90% of students had a higher score than the student.

The composition of a typical group of 200 students taking Stat 200, cross-classified by gender and race, is given in the two-way table below—use the data in this table to answer questions 3-4

<table>
<thead>
<tr>
<th></th>
<th>Asian</th>
<th>Black</th>
<th>Caucasian</th>
<th>Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Males</td>
<td>4</td>
<td>4</td>
<td>68</td>
<td>4</td>
<td>80</td>
</tr>
<tr>
<td>Females</td>
<td>4</td>
<td>8</td>
<td>102</td>
<td>6</td>
<td>120</td>
</tr>
<tr>
<td>Total</td>
<td>8</td>
<td>12</td>
<td>170</td>
<td>10</td>
<td>200</td>
</tr>
</tbody>
</table>

3. The percentage of students who are ‘Black’ is
   a. 6%  b. 15%  c. 45%  d. 60%

4. The percentage of students who are either ‘Male’ or ‘Black’ is
   a. 40%  b. 42%  c. 44%  d. 46%

5. A Type I Error is committed when
   a. We fail to reject the null hypothesis when the null hypothesis is false.
   b. We fail to reject the null hypothesis when the alternative hypothesis is false.
   c. We reject the null hypothesis when the null hypothesis is true.
   d. We reject the null hypothesis when the alternative hypothesis is true.

6. Two ways of collecting data are (i) conducting an experiment, and (ii) doing an observational study. What is the best reason for doing an experiment? Because experiments
   a. Don’t cost as much
   b. Are easier to design and perform
c. Are more socially acceptable  
d. Can give good evidence for causation  

7. Suppose the present success rate in the treatment of a particular psychiatric disorder is 65%. A research group hopes to demonstrate that the success rate of a new treatment will be better than this standard. Which of the following describes a type II error for this problem?  
   a. Claiming that the success rate of the new treatment is greater than 65% when it isn’t.  
   b. Failing to decide that the success rate is greater than 65% when it is.  

Questions 8 through 10 refer to the following information: A researcher wishes to determine the proportion of adults (people 18 or older) in the U.S. who have smoked marijuana at least once. She obtains a simple random sample of 400 adults and determines the proportion among the 400 who say they have smoked marijuana at least once. The result: 256 say they have.  

8. The population of interest to the researcher is  
   a. The 400 people in her study.  
   b. All people in the U.S. who are 18 or older.  
   c. All adults in the U.S. who have smoked marijuana at least once  
   d. The 256 people among the 400 asked who say they have smoked marijuana at least once.  

9. Which of the following statements best summarizes the results of her study?  
   a. The percentage of adults in the U.S. who have smoked marijuana at least once is 64%  
   b. If the study were to be repeated, she would find that 64% of adults in the U.S. have smoked marijuana at least once.  
   c. A higher percentage of males smoke marijuana than females among adults in the U.S.  
   d. The percentage of adults in the U.S. who have smoked marijuana at least once is estimated to be 64%  

10. The ‘95%’ margin of error associated with the proportion of adults who have smoked marijuana at least once is about .05. Which of the following statements can be concluded from this?  
   a. We can be 95% confident that the percentage of adults in the U.S. who have smoked marijuana at least once is not more than 5% from the 64% sample percentage  
   b. The probability is .95 that 64% of adults in the U.S. have smoked marijuana at least once  
   c. The probability is .05 that 64% of adults in the U.S. have smoked marijuana at least once  
   d. Despite the fact that 64% of adults in the U.S. say they have smoked marijuana at least once, at the α = .05 level of significance we cannot statistically conclude that a majority of adults in the U.S. have tried marijuana at least once  

11. Just before presidential elections a polling agency increases the size of its samples from 1000 to 4000. They do this to  
   a. Decrease the standard error of the estimates  
   b. Increase the standard error of the estimates  
   c. Decrease the bias of the results.  
   d. Increase the bias of the results  

12. The weights of adult American men are approximately normally distributed with mean 170 pounds and standard deviation 20 pounds. Half of all adult American men weigh  
   a. Less than 150 pounds
b. Less than 170 pounds
c. Between 150 and 190 pounds
d. Can’t tell because the median isn’t given

Problems 13-15 refer to the following situation. A research study compares two treatments for the common cold. Twenty people are recruited to participate in the study. Ten people are randomly assigned to receive treatment A and the other ten to receive treatment B. The number of hours to get over the cold (according to well-defined criteria) is measured for each person.

13. The response variable in this study is
   a. The number of hours to get over the cold
   b. The twenty people who participate in the study
   c. The two treatments for the cold
   d. The criteria used to determine when each person is over the cold

14. The design used in this study is a
   a. Simple random sample
   b. Stratified random sample
   c. Completely randomized experiment
   d. Randomized block experiment

15. The most appropriate test of significance to use to assess the effectiveness of the two treatments is a
   a. Single-sample t-test
   b. Two-sample t-test
   c. Paired comparison t-test
   d. Two-sample z-test about means or proportions

16. The relationship between men’s actual heights and ideal heights is given approximately by the equation \[ \text{Ideal height} = 24" + 0.7 \times \text{Actual Height} \]. The correlation between the two variables is about .75. Which of the following statements is true, based on the information given between actual and ideal height?
   a. The predicted ideal height of a male who is actually 60" tall is less than 60"
   b. Males who are less than 6'8" (80") in actual height wish they were taller, while those over 6'8" wish they were shorter.
   c. Because the slope of the line is less than one, predicted ideal heights of males are less than their actual heights
   d. 75% of males wish they were taller.

17. A doctor claims he has a cold remedy that will definitely relieve symptoms of the cold. To prove that this is indeed the case, he randomly selects 40 patients with colds and gives them the remedy—30 (or 75%) of the 40 patients report that the remedy definitely relieved the symptoms. Based on these results we can conclude that
   a. The remedy is effective in relieving cold symptoms
   b. Nothing, because we need a much bigger sample
   c. The remedy is better than existing cold remedies
   d. Nothing, because there is no control group

18. An attendee at a party wonders how many chocolate chips there are in the cookies the host is serving. So he randomly picks 5 cookies and counts the number of chips in each cookie as he eats
them. He finds that the number of chips in each of the 5 cookies is 4, 6, 7, 8, and 10. The average number of chips per cookie in his sample is
   a. 6  b. 7  c. 8  d. Can’t say, because he didn’t look at enough cookies.

19. Which of the following statistics is not a measure of variability?

20. A candidate running for Congress claims that 64% of adults in the U. S. favor a tax cut. Her opponent says this is much too high—it is definitely less. To see if this claim has merit, a random sample of 400 adults is asked about it and the percentage favoring a tax cut is obtained. The probability of obtaining the percentage found or an even lower one turns out to be .032, or a 3.2% chance, if one calculates this probability assuming the claim is true. If we test an hypothesis about the candidate’s claim with a .05 significance level, based on the outcome of the polling, we should
   a. Draw no conclusions and get a bigger sample
   b. Conclude that the percentage of adults favoring a tax cut is between 60.8% and 67.2%.
   c. Reject the candidate’s claim
   d. Not reject the candidate’s claim

21. A 95% confidence interval for a population proportion p, based on a sample of size 100 would be
   a. wider than the confidence interval if the sample size had been 400
   b. shorter than the confidence interval if the sample size had been 400
   c. the same as the confidence interval if the sample size had been 400
   d. can’t say

22. Which of the following statistics is not a measure of location?
   a. Median  b. Standard deviation  c. Trimmed Mean  d. Mean

23. Randomization is an important part of experimentation. The reason for this is that
   a. If you do not randomize you will get random answers.
   b. If you randomize you will get random answers.
   c. If you randomize the effects of confounding variables and/or bias will tend to be minimized.
   d. If you do not randomize, the effects of confounding variables and/or bias will tend to be minimized

24. Null and alternative hypotheses are generally statements about
   a. populations
   b. samples
   c. both populations and samples
   d. neither populations nor samples
APPENDIX H

CORRELATION MATRICES
## Correlation Matrix of Variables in Individual Factor-Attitude toward Statistics

<table>
<thead>
<tr>
<th></th>
<th>A01</th>
<th>A02</th>
<th>A11</th>
<th>A14</th>
<th>A21</th>
<th>A25</th>
<th>A03</th>
<th>A07</th>
<th>A10</th>
<th>A12</th>
<th>A16</th>
<th>A19</th>
<th>A04</th>
<th>A06</th>
<th>A18</th>
<th>A22</th>
<th>A26</th>
<th>A28</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A01</strong></td>
<td>1</td>
<td>.219</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A02</strong></td>
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<td>.273</td>
<td>.390</td>
<td></td>
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<td>0.206**</td>
<td>0.202**</td>
<td>0.739**</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13. Final</td>
<td>0.218**</td>
<td>0.311**</td>
<td>0.148*</td>
<td>0.095</td>
<td>-0.103</td>
<td>-0.022</td>
<td>-0.155*</td>
<td>-0.037</td>
<td>0.171**</td>
<td>0.215**</td>
<td>0.535**</td>
<td>0.666**</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>14. Knowledge</td>
<td>0.050</td>
<td>0.137*</td>
<td>0.197**</td>
<td>0.018</td>
<td>-0.089</td>
<td>-0.022</td>
<td>-0.088</td>
<td>0.012</td>
<td>0.137*</td>
<td>0.147*</td>
<td>0.304**</td>
<td>0.408**</td>
<td>0.393**</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Mean: 5.02 29.52 47.72 27.25 10.97 14.30 13.38 16.23 73.85 184.54 208.31 112.17 163.60 17.05
SD: 34 6.09 6.73 5.04 4.01 4.36 3.56 3.82 1.66 7.20 17.94 16.50 20.79 3.11

Note. ** significant at the 0.01 level; * significant at the 0.05 level
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Education

Ph.D., Instructional Systems, The Pennsylvania State University. 2006
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Publication and presentations


