Factors Related to Math Performance and Potential Benefits of One-on-One Instruction

The Honors Program
Senior Capstone Project
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ABSTRACT

This fall 2010 study of Bryant University students enrolled in freshman-level math courses considered factors related to college-level math performance, including gender, math self-efficacy, math anxiety, and utilization of professors' office hours and/or tutoring center services. Female students at Bryant reported lower levels of math self-efficacy and higher levels of math anxiety, both of which research has shown to be negatively correlated with test scores. The use of one-on-one instruction was expected to provide a potential counterweight to this equation. Results from the 287 initial and 229 final surveys administered in this study did not support this hypothesis. This phenomenon was interpreted and potential solutions to the gender problem in mathematics were explored.

INTRODUCTION

Studies show that female students (middle school-aged and older) tend to have lower math self-efficacy than male students (Pajares & Miller, 1994). It is known that low math self-efficacy is positively related to heightened math anxiety (Jain & Dowson, 2009). Research also shows that increased math anxiety drives students to seek one-on-one instruction from professors (May & Glynn, 2008). This study incorporated these three models for Bryant University students with all levels of math ability enrolled in freshman-level math courses and examined how the four variables of gender, math self-efficacy, math anxiety, and use of one-on-one instruction can be used to predict math performance. The study sought to show through data and descriptive analysis that the negative effects on performance caused by low math self-efficacy and high math anxiety can be offset to some degree by meeting with the professor or using the math services provided by the University's tutoring center prior to an exam. Particular attention was given to how these relationships varied with gender. Participants were primarily Bryant University 2010 incoming freshmen with initial math class placements of all math ability levels; some classes surveyed included non-first year students. Quantitative and descriptive data were collected after each class's first and third exams through an in-class survey. The survey was based on one created and used by Professor Richard Smith and Professor Phyllis Schumacher in math placement, and one adapted and used by Professor Nancy Betz of Ohio State University measuring math anxiety (1978).

Abundant research (Betz, 1978; Hoffman, 2010; Jain & Dowson, 2009; May & Glynn, 2008; Pajares & Miller, 1994) has been done on the relationships between gender and math self-efficacy, gender and math anxiety, math self-efficacy and math anxiety, and math anxiety and time students spend one-on-one with their professors or in tutoring sessions. This study examined how these independent variables, as well as use of on-campus math tutoring services, relate when considered all together, and how they contribute to math performance. Students were categorized based on their math abilities and measured by their initial class placements.

This study provides support to professors and tutors on how to counsel students better. Professors and tutors can better prepare methods/strategies on how to help students achieve higher test scores than if they did not seek help outside of class if the professors and tutors know that by meeting with students they can reduce the effects of those students' math anxiety.

If professors and tutors know that by meeting with students, they can reduce the effects of those students' math anxiety and, thus, help them achieve higher test scores than if they did not seek help outside of class, they can better prepare methods/strategies on how to accomplish this. The immediate effects this would have on these students (the higher test scores) will be a stepping-stone to solving the real issue at hand. Due to their low math self-efficacy, women are less likely to enter the field of mathematics (O'Brien et al., 1999). To achieve a more balanced gender ratio in math-related careers and maintain that of math majors, professor and tutor intervention may prove key. During one-on-one sessions, professors and tutors may be able to reverse the effects of low math self-efficacy and high math anxiety on both students' test scores and career aspirations by offering some balance of encouragement and instruction to students.

LITERATURE REVIEW

Two central constructs in this research were math self-efficacy and math anxiety. A widely accepted definition of math anxiety is provided by Richardson and Suinn (1972): "Mathematics anxiety involves feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (p. 551). According to Pajares and Miller (1994), math self-efficacy is the assessment "of individuals' judgments of their capabilities to solve specific math problems, to perform math-related tasks, and to succeed in math-related courses" (p. 194).

Gender, Math Self-Efficacy, and Math Performance

In their 1994 study, Pajares and Miller addressed the nature of the relationship between math self-efficacy and math performance and how the strength of the relationship differed for male and female students. In particular, they examined the mediating effect of self-efficacy on gender and prior experience on both the common mechanisms and problem-solving performance. Participants in the study were 350 undergraduate students, the majority of whom were female, from a large public university in the southern United States. To measure math self-efficacy, Pajares and Miller (1978) used the 5-point Likert scale adaptation of Dowling's Mathematics Confidence Scale (MCS) created by Langenfeld and Pajares (1992). They measured perceived usefulness of mathematics by adapting the 20-item instrument created by Shell, Murphy and Bruning (1989). Betz's (1978) adaptation of the Mathematics Anxiety Scale (MAS) was used to measure math anxiety. A 180-item Self Description Questionnaire (SDQ) was used to measure math self-concept. Math performance was measured by the Mathematics Problems Performance Scale (MPPS) developed by Dowling (1978). The study was conducted in one-period time frames in individual classes. The self-efficacy, perceived usefulness, self-concept, and anxiety measures were given and collected prior to the administration of the performance measure. In the path model tested, gender was hypothesized to influence all variables and math self-efficacy would mediate this influence on performance (Pajares & Miller, 1994). Math self-efficacy was identified as the strongest direct predictor of math performance. Gender was determined to have a strong influence on math self-efficacy, and, through that variable, it had strong indirect effects on math performance. Male students had higher math self-efficacy and higher average math performance scores than the female students. Pajares and Miller concluded from their study:

> If self-efficacy is an important predictor of performance and is a primary cause of feelings of self-worth and perceived usefulness, then efforts to identify, understand, and alter inaccurate judgments should prove beneficial. Moreover, if self-efficacy beliefs are major mediators of behavior and behavior change, then counseling interventions designed to change behavior are useful to the degree that they increase the self-efficacy beliefs related to the behavior in question. The math competence of many undergraduates, for example, may tell us very little about math self-efficacy, and it is the latter factor that will be critical in their choice of math-related decisions such as pursuing math courses, majors, or careers (p. 201).

This supports the hypotheses of the current study that female students will report lower levels of math self-efficacy than male students, and that math self-efficacy and math test score are positively correlated. Pajares and Miller emphasized the potential for improvement in math performance through intervention designed to address the low self-efficacy of female students; the researchers' ultimate intension was to achieve a more gender-balanced ratio in the field of mathematics.

Gender and Math Anxiety

Earlier research by Nancy Betz explored the effect math anxiety has on math performance and how gender influences that relationship. In her 1978 study, Betz sought to assess the prevalence and severity of math anxiety in college students; to evaluate gender, age, and prior preparation in math as predictors of math anxiety; and to identify significant relationships between math anxiety and math ability, general anxiety, and test anxiety. To accomplish this, Betz used a modified version of the Mathematics Anxiety scale created by Fennema and Sherman (1976). She also measured trait anxiety and test anxiety using instruments created by Spielberger, Gorsuch and Lushene (1970) and C.D. Speilberger (1980), respectively. Each student's American College Test (ACT) score was considered. In addition, a supplementary questionnaire was administered to obtain the subjects' backgrounds and demographic information. The subjects were 652 primarily freshman and sophomore students from Ohio State University enrolled in a basic math course, an advanced math course, or an introductory psychology course. Overall, students in the advanced math course reported less math anxiety than students in both the basic math course and the introductory psychology course. This was especially true for female students, who reported greater levels of math anxiety than did males, in all but the advanced math course (where they reported levels equal to their male classmates). Although Betz did not mention the relationship between age and math anxiety level for male students, she did reveal that the older female students in her study tended to be more math anxious than the younger female students. Math anxiety for all groups and both genders was most commonly indicated when questions about math tests were asked, illustrating that math anxiety has its greatest impact during test time. As expected, there was also a positive relationship between math anxiety and other forms of anxiety detected; meaning, students prone to anxiety were more prone to math anxiety than were their classmates. Her results, thus, suggest that average level of math anxiety, like math self-efficacy, differs across gender, especially for the most at-risk students. It is important to note, however, that when Pajares and Miller (1994) conducted their study, they considered the impact of math anxiety on math performance, but concluded that it was less significant a factor than was math self-efficacy.

Math Self-Efficacy and Math Anxiety

Following the results of the Betz (1978) and Miller and Pajares (1994) studies, one begins to wonder about the nature of the relationship between math self-efficacy and math anxiety. This was the focus of Jain and Dowson's 2009 study of 232 Indian eighth-grade students from English language schools. They sought to prove that self-regulation is positively related to enhanced self-efficacy, which, in turn, is positively related to reduced math anxiety. Jain and Dowson recognized the impact age and gender could have on the test variables; nearly 60 percent of their subjects were male, and as they were all in eighth grade, the mean age of the participants was 13.3 years. Unlike as would be the case in Western schools, where the schooling system is more uniform, however, the eighth-graders' ages ranged from 12 to 15 years. Besides a standard questionnaire to determine demographic information, a 55-item Motivated Strategies for Learning Questionnaire created by McKeachie, Pintrich, and Lin (1985), and the Mathematics Anxiety Scale created by Fennema and Sherman (1976) were used. Important results of this study included the necessary intervention of enhanced self-efficacy in the positive relationship between self-regulation and reduced math anxiety, which led Jain and Dowson to conclude that "by remaining focused on the instructional ('teaching') task of developing students' strategic capacities, teachers can expect positive impacts on students' self-perceptions of ability and subsequent reductions in mathematics anxiety" (p. 246). Jain and Dowson did point out several limitations to their study, namely the lack of longitudinal data and the inability to make cross-cultural and cross-system comparisons, but they also asserted that their findings were consistent with those of Western university-level students. That is, older and female students reported higher math anxiety overall than did younger and male students. This was in agreement with Betz's results (1978). The results of this study support the hypothesis that math self-efficacy and math anxiety are negatively correlated.

Gender, Math Self-Efficacy, Math Anxiety, and Math Performance

The degree of impact of math self-efficacy and math anxiety on math performance was the focus of Hoffman's 2010 study. He stated that his goal was to determine "the role of self-efficacy beliefs and mathematics anxiety in mathematics problem-solving efficiency" and to determine if "the impact of these variables differ contingent upon level of problem complexity and working memory capacity (WMC)" (p. 276). He had students answer 40 mental multiplication problems at varying levels of difficulty. Anticipating only minimal gender differences, Hoffman "expected as problem complexity increased participants with higher mathematics anxiety and lower self-efficacy would show a decrease in problem-solving accuracy and problem-solving efficiency" (p. 278). Participants included both undergraduate and graduate students at two large southeastern universities. Betz's (1978) Mathematics Anxiety Scale was used to measure the students' math anxiety. Self-efficacy was determined by averaging a student's self-reported confidence level in solving eight of the questions. Using Cronbach's alpha, the reliability of the math anxiety and self-efficacy measures was confirmed as high. When solving the more complex problems, male students answered more questions correctly than the female students and were more efficient in doing so. Male students were also found to have significantly higher levels of math self-efficacy than the female students. In addition, "a positive relationship between self-efficacy and problem-solving accuracy and problem-solving efficiency was found," and "significant negative relationships between mathematics anxiety and self-efficacy were observed" (Hoffman, 2010, p. 279). These results were consistent with those found by Betz (1978) and Jain and Dowson (2009). They also supported the contention made by the Center for Positive Practices (2005) that gender is not an independently strong predictor of mathematics performance, but it is an influential source of mathematics self-efficacy, which strongly predicts and mediates math performance. It was hypothesized in the current study that female students tend to have lower math self-efficacy than male students, higher math anxiety than males, and, consequently, lower test scores than males. If this proved to be true, the potential for intervention first discussed by Pajares and Miller becomes all the more important.

<u>Math Self-Efficacy, Math Anxiety, and Use of Professors' Office Hours</u>

One such occasion for this intervention is during professors' office hours. In the pilot administration of their newly-developed Mathematics Self-Efficacy Questionnaire (MSEQ), May and Glynn (2008) asked seventy undergraduate non-mathematics majors "30 Likert-type items that provided information about students' self-efficacy in relations to factors such as their gender, previous mathematics achievement, previous mathematics experiences, their use of self-regulation learning strategies, and their perceived level of mathematics anxiety" (para. 1). The questionnaire was administered online and given to non-mathematics majors, specifically, to find trends in the academic habits of those with the lowest levels of math self-efficacy. Results of questions concerning tests were similar to those of Betz's study (1978) in that math anxiety was reported to be highest around test time. In addition, high math anxiety and low math self-efficacy were found to be positively related to the number of hours students spent getting one-on-one help from professors. As expected, five students who were chosen to be interviewed to discuss their interpretations of the study reported that seeking help from professors outside of class could improve their grades. Thus, May and Glynn ended their paper emphasizing the importance of one-on-one instruction in helping math students to feel comfortable with the subject so that they can succeed in it. The hypothesis that math anxiety and number of hours spent getting one-on-one instruction from professors are positively correlated, was formulated largely from the results of this study by May and Glynn.

Use of Professors' Office Hours to Improve Academic Performance

With high math anxiety, a known cause of lower test scores, being lowered by visits with the professor, it was reasonable to predict that number of hours spent getting one-on-one instruction from professors and test score would be positively correlated. Thus, it was not surprising that the positive relationship between the use of the professor's office hours and student performance (grades) that the student interviewees in May and Glynn's study (2008) hypothesized was echoed by Jacobs and Hyman (2009) in their suggested "15 Secrets of Getting Good Grades in College." With "Secret 11: 'Hook up' with the prof.," these two professors suggests that office hours are the resource "most likely to benefit your grade" in college (para. 13).

Use of Tutoring Center Services to Improve Academic Performance

A second, and perhaps more frequent, occasion for intervention targeting low math self-efficacy and high math anxiety is during the use of tutoring center (TC) services provided by the University. Cooper (2010) found a similar positive relationship between the use of tutoring center services and student performance as others (Jacobs & Hyman, 2009; May & Glynn, 2008) found between the utilization of professors' office hours and student performance. He conducted his study at Western Washington University, where tutoring is performed in a "drop-in" style, such that students use the TC as a study area and tutors are available on a first-come-first-serve basis when questions arise. As at Bryant University, tutors are primarily upperclassmen who excel in the subjects they tutor, and who have completed a certified College Reading and Learning Association training program. TutorTrac software is used at both Bryant and Western Washington to monitor students' usage of TC services. Cooper evaluated the effect of TC services on persistence, academic standing, and cumulative grade point average, having grouped the students by their usage expressed as number of individual visits to the TC. Those who visited the center 10 times or more during a quarter (an average of once per week), were considered the "high use group." He also distinguished between those who used the center less than 10 times during a quarter and those who did not use it at all. The results of Cooper's study indicated that using the TC services more than 10 times per semester has a significant positive effect on a student's persistence and academic standing. The increase in persistence was also true for those who visited the center fewer than 10 times; but the increase in academic standing for these students was not significant. Those students who visited the TC more than 10 times had a significantly higher cumulative GPA than did students who did not visit the TC or who visited fewer than 10 times, controlling for race/ethnicity, SAT score, and high school GPA. While the effect of the use of TC services on a grade in a particular class could not be determined, the study showed that a correlation does exist between student visits and cumulative GPA for the following quarter, which, Cooper suggested, "may be indicative of successful tutoring" (p. 33). Thus, it was hypothesized in the current study that, like number of hours spent getting one-on-one instruction from math professors', the number of hours spent getting one-on-one instruction from tutoring center staff is positively correlated with test score. As in Cooper's study, it was understood that results may not be realized within one semester. Follow-up studies in subsequent semesters are expected to reveal similar test score and tutoring center utilization trends at Bryant as were found at Western Washington University.

<u>Gender, Math Self-Efficacy, and Quantitative Career Interest</u>

Ultimately, the problem at the core of the math anxiety/self-efficacy issue is the significant lack of female interest and participation in math-related careers. O'Brien, Martinez-Pons and Kopala (1999) hypothesized that deficits in self-efficacy or self-perceived skill in mathematics, essential in careers in quantitative fields, might contribute to the low numbers of women in the fields of science and engineering. The participants in the study were 415 eleventh-grade students (221 boys and 194 girls) from twelve parochial schools in a large metropolitan area. To measure math self-efficacy, they used a version of the Mathematics

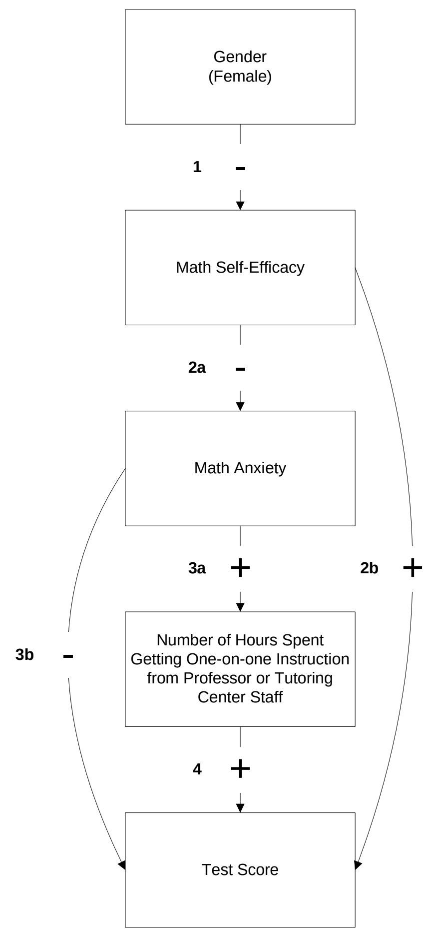
Self-Efficacy Scale (MSES) developed by Betz and Hackett (1983), which they adapted for use with high school students. Career interest in science and engineering was measured by the Jackson Vocation Interest Survey (JVIS) (Jackson, 1977). Path analysis was used to test the model. Science-math self-efficacy was determined to be the sole significant predictor of career interest in science. While gender did have an influence on students' career interests in science and engineering, "the mediating roles…of self-efficacy…emphasize the need to focus on [this] key intervening [process] in any attempt to address the problem of lowered female…participation in science and engineering" (O'Brien et al., 1999, p. 235). Thus, once again, it is imperative that math professors and tutoring center staff use their time with students to address the factors that affect test score and, ultimately, career interest.

HYPOTHESES & RESEARCH OBJECTIVE

In the present study, several hypotheses were tested through the use of survey data in order to address the question as to how a college student's math performance is influenced by his or her level of math self-efficacy, math anxiety, and utilization of professors' office hours or tutoring center services. As was found to be the case in Pajares and Miller's (1994) study, females were expected to be more likely to report low levels of math self-efficacy than were males. Math self-efficacy is negatively correlated with math anxiety (Jain & Dowson, 2009) and positively correlated with math test scores (Pajares & Miller, 1994; Hoffman, 2010). Because female students tend to report higher levels of math anxiety than male students (Betz, 1978), it was anticipated that female students would perform poorer than male students on math tests and in math courses. Unfortunately, this in turn could result in their being disinterested in quantitative careers (O'Brien et al., 1999). Of course, this must be prevented if possible. Thus, with math anxiety being positively correlated with the number of hours spent getting one-on-one instruction from the professor and/or tutoring center staff (May & Glynn, 2008) and negatively correlated with test score (Betz, 1978), it should be addressed during those one-on-one sessions. While it was expected that number of hours spent getting one-on-one instruction from the math professor and/or tutoring center staff is positively related to test score, this is through intervention targeting low math self-efficacy and high math anxiety.

The ultimate objective of this study was to determine whether the positive effects of getting one-on-one instruction prior to a math exam are able to outweigh the negative effects of low math self-efficacy and high math anxiety. This was tested for instruction given by both the professor and tutoring center staff and at all levels of math ability.

For a visual representation of the model tested in this study, please see Figure 1.



1. Females are more likely to have low math self-efficacy than are males.
2. Math self-efficacy is
    a. negatively correlated with math anxiety.
    b. positively correlated with math test scores.
3. Math anxiety is
    a. positively correlated with the number of hours spent getting one-on-one instruction from the math professor or tutoring center staff.
    b. negatively correlated with math test scores.
4. Number of hours spent getting one-on-one instruction from the math professor or tutoring center staff is positively correlated with test scores.

Figure 1 – Test Model

PROCEDURES

Data Collection

Survey Design

With the permission of Professor Richard Smith, its creator, a revised version of several questions from the "Freshman Survey" that is given upon completion of the math placement exam prior to freshman orientation was used after the first math exam of the semester. Questions to determine perceived math self-efficacy and perceived math anxiety utilized a Likert scale with five options, with the left-most representing "Strongly Agree" and right-most representing "Strongly Disagree," and was formed under the guidance of Professor Allison Butler of the Applied Psychology Department and Professor Phyllis Schumacher of the Mathematics Department at Bryant University with Nancy Betz's scale at its base (1978). Approximately half of these questions were positively-phrased, and half were negatively-phrased. The order of positively and negatively-worded questions and math self-efficacy and math anxiety questions was random. Cronbach's alphas of 0.92 and 0.84 for the math anxiety and math self-efficacy scales, respectively, showed them to be internally consistent. Initial class placement, gender, and major were reported using multiple-choice questions. An estimate of hours spent getting one-on-one help from the professor; an estimate of hours spent getting one-on-one help for math at Bryant University's tutoring center, the Academic Center for Excellence (ACE); an estimate of hours spent studying; and first math test score were reported using open-ended questions.

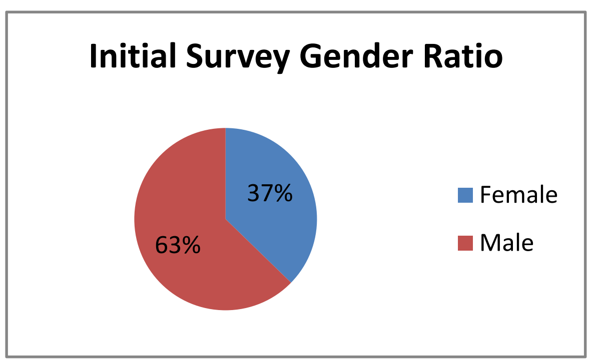
A second survey was administered following the third math exam of the semester. The only new questions on this second survey were revised versions of those open-ended questions from the initial survey concerning hours getting one-on-one help, a multiple-choice question to distinguish freshman from non-first-year students, and a request for third math test score.

Survey Administration

Professors of all levels of freshman math courses were emailed and asked for permission for the author of this study to enter their classrooms to conduct a two-part paper-based survey that would take approximately five minutes of class time. The professors were given a brief overview of the purpose of the author's study, but asked not to share that information with their students. Once permission was granted, a range of early morning (5 sections), late morning (5 sections), and night (1 section) classes were selected for survey administration. (Ideally, afternoon courses would also have been included, but the administration of surveys was impossible for the author during that time of day.) The initial surveys were administered primarily during the seventh week of classes, and the follow-up surveys were administered primarily during the fourteenth week of classes. Participation in the surveys was voluntary for students and a consent form was signed by each student who chose to participate. Although they were not told of the objective of the study, the students were informed that the research was for the author's honors thesis and were invited to hear her findings during the Honors Colloquium.

Participants

Participants in the study were students drawn from freshman-level math courses at Bryant University. The selection of students was on an initial math class-basis with the permission of the instructor. With most participants being first-year students, they were expected to be primarily between the ages of 18 and 19 years old. No inquiries were made as to the participants' race, nationality, or first language, but it was expected that the sample was representative of Bryant University's overall demographics. All levels of math ability were represented with surveys being given in Enriched Mathematical Reasoning I (MATH-E105), Mathematical Reasoning I (MATH-105), Honors: Finite Mathematics (MATH-107), Mathematics of Finance (MATH-129), Calculus and Analytic Geometry I (MATH-121), and Calculus and Analytic Geometry II (MATH-122) classes. For a representative sample of students across math ability levels, it was intended that, with full attendance and participation in the sections chosen, 71 MATH-E105, 129 MATH-105, 16 MATH-107, 35 MATH-129, 62 MATH-121, and 28 MATH-122 students would participate.



Of the 287 usable initial surveys, 107 (37%) were taken by female students and 180 (63%) were taken by male students. This is almost exactly the same ratio as the Bryant population, which is 60% male and 40% female (Bryant, 2011). Fifty-seven (20%) participants were enrolled in MATH-E105, 104 (36%) were enrolled in MATH-105, 16 (6%) were enrolled in MATH-107, 30 (10%) were enrolled in MATH-129, 58 (20%) were enrolled in MATH-121, and 22 (8%) were enrolled in MATH-122 (see Figure 2).

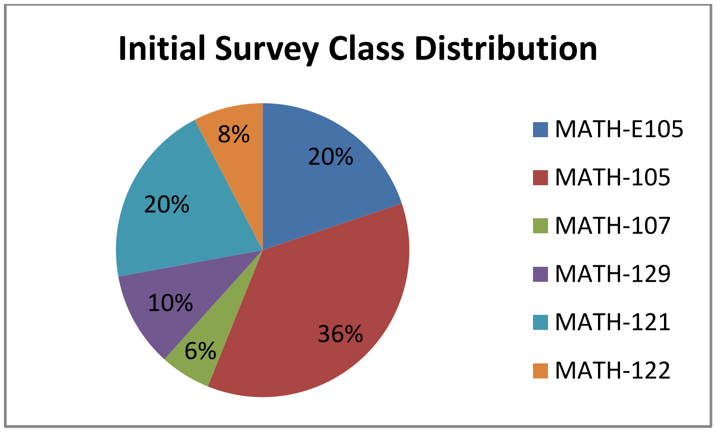
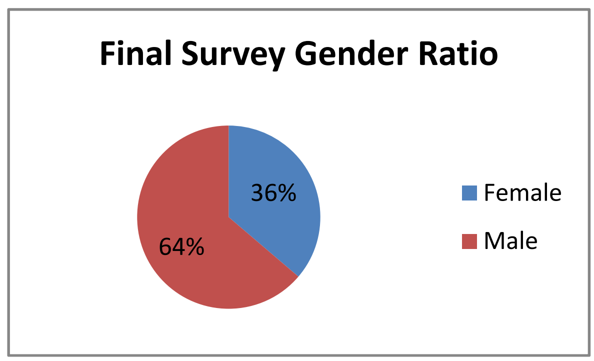


Figure 2 – Initial Survey Class Distribution

Of the 229 usable final surveys, 83 (36%) were taken by female students and 146 (64%) were taken by male students. Thirty-eight (17%) participants were enrolled in MATH-E105, 82 (36%) were enrolled in MATH-105, 14 (6%) were enrolled in MATH-107, 30 (13%) were enrolled in MATH-129, 44 (19%) were enrolled in MATH-121, and 21 (9%) were enrolled in MATH-122 (see Figure 3). This drastic decrease in the number of participants from nearly all of the courses coincided with a decrease in attendance during the second half of the semester reported to the author by the professors of these courses.



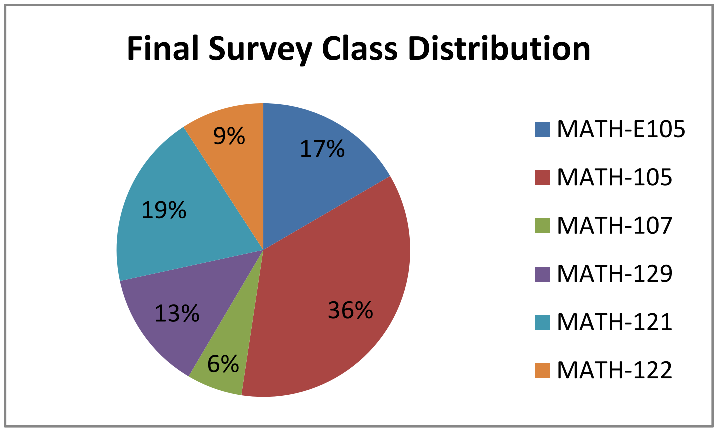


Figure 3 – Final Survey Class Distribution

Measures

The dependent variable in this study was math performance, with TEST representing math test scores. The independent variables considered were initial class placement (CLASS: MATH-E105=1, MATH-105=2, MATH-107+MATH-129=3, MATH-121+MATH-122=4); gender (GENDER: Male=1, Female=0); perceived math self-efficacy (MSE); perceived math anxiety (MA); student's estimate of hours spent meeting with the professor prior to the exam (PROF); student's estimate of hours spent utilizing the University tutoring center's math services (ACE); and the student's estimate of hours spent studying prior to the exam (STUDY). Initial class placement is based on math placement test score, math and verbal SAT (or equivalent) scores, AP Calculus test score(s) (if applicable), high school GPA, and major; and is intended by the University as a measure of incoming freshmen math ability. At Bryant University, MATH-E105 students are considered to be of the lowest ability; MATH-105 students are considered to be of average math ability; MATH-107 and MATH-129 students are considered to be of high math ability enrolled in non-calculus courses; and MATH-121 and MATH-122 students are considered to be of high math ability and calculus students.

Data Analysis

Once the surveys were collected, all data were inputted into excel for preparation/manipulation for analysis. Any incomplete data was left blank. Any obviously incorrect data (i.e. multiple answers selected for one question) were made blank. A common issue occurred with the reporting of letter grades despite the request for "numeric grades."

This was corrected with the understanding that an A+ was converted to a 98, an A was converted to a 95, an A- was converted to a 91, a B+ was converted to an 87, a B was converted to an 84, a B- was converted to an 81, a C+ was converted to a 77, a C was converted to a 74, a C- was converted to a 71, a D+ was converted to a 67, a D was converted to a 64, and an F was converted to a 60. Please note, this coding of a reported score of F as 60 may account for a slightly higher average of the variable TEST. In addition, when students failed to report the number of hours of one-on-one instruction they received, but instead reported the frequency (i.e. "weekly"), their responses were converted to values under the assumption that the reported frequency was consistent and that each visit lasted approximately one hour.

As suggested in the "Measures" section above, both descriptive and quantitative data were considered in this study. To begin, descriptive data were reported in percentages in each category, while the mean, variance, and standard deviation were reported for quantitative data.

Statistical testing procedures were then conducted to test the hypotheses using MINITAB software. A one-tailed *t*-test was used to test the relationship between gender and MSE. Female students were expected to have reported lower levels of math self-efficacy than male students. The correlation coefficient between MSE and MA was calculated, and expected to be negative. In contrast, the correlation coefficient between MSE and TEST was calculated and expected to be positive. Next, the correlation coefficients between MA and PROF and MA and ACE were calculated and were expected to be positive as well. The correlation coefficient between MA and TEST when then calculated, was expected to be negative. The correlation coefficients between PROF and TEST and ACE and TEST, however, were calculated next and were expected to be positive. One-way ANOVAs were also used to determine if there were differences among means for the quantitative variables of MA, MSE, TEST, STUDY, PROF, and ACE by CLASS (ability).

Following the testing of the individual hypotheses, the ultimate research objective of determining the power of one-on-one instruction (PROF and/or ACE) to counter the negative effects of low math self-efficacy and high math anxiety was tested using a stepwise model to eliminate multicollinearity, because it is known that a strong correlation exists between MSE and MA. GENDER and STUDY were included as independent variables in these tests. In addition, all tests were performed for both the initial survey data and the final survey data to see if there were any changes in the strength of the relationships later in the semester.

RESULTS

The initial survey data was first considered for analysis alone. Then, the results of the final survey were compared to those results. The following statistical results were obtained using MINITAB and the statistical output can be found in the Appendix.

Results of ANOVAs for Quantitative Variables by Class					
MA	$\bar{x}_1$=3.0193	$\bar{x}_2$=2.7192	$\bar{x}_3$=2.4239	$\bar{x}_4$=2.2413	*p*-value=0.000
MSE	$\bar{x}_1$=3.1298	$\bar{x}_2$=3.4019	$\bar{x}_3$=3.7174	$\bar{x}_4$=3.7725	*p*-value=0.000
TEST	$\bar{x}_1$=81.46	$\bar{x}_2$=84.81	$\bar{x}_3$=82.90	$\bar{x}_4$=74.15	*p*-value=0.000
PROF	$\bar{x}_1$=0.383	$\bar{x}_2$=0.103	$\bar{x}_3$=0.120	$\bar{x}_4$=0.666	*p*-value=0.006
ACE	$\bar{x}_1$=1.546	$\bar{x}_2$=0.376	$\bar{x}_3$=0.196	$\bar{x}_4$=1.177	*p*-value=0.024
STUDY	$\bar{x}_1$=2.849	$\bar{x}_2$=1.845	$\bar{x}_3$=2.159	$\bar{x}_4$=4.156	*p*-value=0.000

In the initial survey case, there were significant differences (with α=.05) between the class means for MA (p=0.000), MSE (p=0.000), TEST (p=0.000), STUDY (p=0.000), PROF (p=0.006), and ACE (p=0.024). Students with low math ability (CLASS 1) reported significantly higher levels of math anxiety ($\bar{x}_1$=3.0193) than students from both of the classes with high math ability (CLASS 3 and CLASS 4) ($\bar{x}_3$=2.4239, $\bar{x}_4$=2.2413). Furthermore, students with an average level of math ability (CLASS 2) reported significantly higher levels of math anxiety ($\bar{x}_2$=2.7192) than the students in the calculus courses (CLASS 4). Students with low math ability also reported significantly lower levels of math self-efficacy ($\bar{x}_1$=3.1298) than did both classes with high math ability ($\bar{x}_3$=3.7174, $\bar{x}_4$=3.7725). In addition, students with an average level of math ability reported significantly lower levels of math self-efficacy ($\bar{x}_2$=3.4019) than the students in both high math ability courses. Interestingly, in the initial case, the calculus students reported test scores significantly lower ($\bar{x}_4$=74.15) than those reported by the other three groups ($\bar{x}_1$=81.46, $\bar{x}_2$=84.81, $\bar{x}_3$=82.90). These calculus students also reported significantly higher numbers of hours devoted to studying for the first exam ($\bar{x}_4$=4.156) than both the other non-calculus high-level math students and the average level math students ($\bar{x}_2$=1.845, $\bar{x}_3$=2.159). They reported significantly greater use of professor office hours ($\bar{x}_4$=0.666) than the average-level math students ($\bar{x}_2$=0.103) as well. The low-level math students, in contrast, reported the highest use of ACE services ($\bar{x}_1$= 1.546), but those were not significantly greater than those reported by the calculus students ($\bar{x}_4$=1.177).

Results of *T*-tests for Quantitative Variables by Gender			
MA	$\bar{x}_0$=2.735	$\bar{x}_1$=2.517	*p*-value=0.010
MSE	$\bar{x}_0$=3.378	$\bar{x}_1$=3.576	*p*-value=0.006
TEST	$\bar{x}_0$=80.0	$\bar{x}_1$=81.2	*p*-value=0.241
PROF	$\bar{x}_0$=0.47	$\bar{x}_1$=0.22	*p*-value=0.038
ACE	$\bar{x}_0$=0.77	$\bar{x}_1$=0.82	*p*-value=0.554
STUDY	$\bar{x}_0$=2.86	$\bar{x}_1$=2.68	*p*-value=0.352

Gender proved to be a significant factor in these initial surveys (with α=.05) when considered with MA (*p*=0.010), MSE (*p*=0.006), and PROF (*p*=0.038). Females reported higher levels of math anxiety than males ($\bar{x}_0$=2.735, $\bar{x}_1$=2.517), lower levels of math self-efficacy than males ($\bar{x}_0$=3.378, $\bar{x}_1$=3.576), and greater number (though still very small) of hours spent receiving one-on-one instruction from their professors ($\bar{x}_0$=0.47, $\bar{x}_1$=0.220). Surprisingly, however, the difference between mean test scores for male and female students were not significantly different ($\bar{x}_0$=80.0, $\bar{x}_1$=81.2, *p*=0.241), though, as expected, males had higher test scores than females.

Results of *T*-tests for Use of One-on-one Instruction			
MA	$\bar{x}_{\text{Go To ACE (0)}}$=2.458	$\bar{x}_{\text{Go To ACE (1)}}$=3.024	*p*-value=0.000
MA	$\bar{x}_{\text{Saw Prof (0)}}$=2.564	$\bar{x}_{\text{Saw Prof (1)}}$=2.742	*p*-value=0.065

In a further investigation of the characteristics of students seeking one-on-one instruction, it was determined that whether or not students go to see a professor during office hours or go to ACE for tutoring services (at all) were significantly related to their reported levels of math anxiety. With a *p*-value of 0.065, and significance at the α=0.10 level, those who sought help from the professor reported higher levels of math anxiety ($\bar{x}_1$=2.742) than those who did not seek their professors' help ($\bar{x}_0$=2.564). Similarly, with a *p*-value of 0.000, and significance at the α=0.001 level, those who sought help at ACE reported higher levels of math anxiety ($\bar{x}_1$=3.024) than those who did not seek the help of tutors ($\bar{x}_0$=2.458).

Correlation Matrix

	MA	MSE	TEST	PROF	ACE	STUDY
MA	*r*=1.000	*r*=-0.768 *p*=0.000	*r*=-0.280 *p*=0.000	*r*=0.085 *p*=0.153	*r*=0.193 *p*=0.001	*r*=0.135 *p*=0.024
MSE	*r*=-0.768 *p*=0.000	*r*=1.000	*r*=0.336 *p*=0.000	*r*=-0.066 *p*=0.267	*r*=-0.140 *p*=0.019	*r*=-0.099 *p*=0.098
TEST	*r*=-0.280 *p*=0.000	*r*=0.336 *p*=0.000	*r*=1.000	*r*=-0.085 *p*=0.167	*r*=-0.157 *p*=0.010	*r*=-0.110 *p*=0.072
PROF	*r*=0.085 *p*=0.153	*r*=-0.066 *p*=0.267	*r*=-0.085 *p*=0.167	*r*=1.000	*	*
ACE	*r*=0.193 *p*=0.001	*r*=-0.140 *p*=0.019	*r*=-0.157 *p*=0.010	*	*r*=1.000	*
STUDY	*r*=0.024 *p*=0.024	*r*=-0.099 *p*=0.098	*r*=-0.110 *p*=0.072	*	*	*r*=1.000

*Not tested

Almost all of the tested correlations were significant at the α=.10 level, and most were significant at the α=.05 and α=.001 levels. As expected, math anxiety and math self-efficacy were negatively correlated with *p*=0.000. Math anxiety and test score were also negatively correlated with *p*=0.000. Math anxiety and study hours were positively correlated with *p*=0.024, as were math anxiety and ACE hours with *p*=0.001. In contrast, math self-efficacy and test score were positively correlated with *p*=0.000. Math self-efficacy was also negatively correlated with study hours and ACE hours with *p*=0.098 and *p*=0.019, respectively. Unexpectedly, study hours and ACE hours were also negatively correlated with test score with *p*=0.072 and *p*=0.010, respectively. When a two-tailed *t*-test was run for initial test scores and utilization of any form of one-on-one instruction (professors' office hours and/or tutoring center services), it was found that those who went had a mean test score of 82.8 and those who did not had a mean test score of 75.8, with the difference being significant (*p*=0.000). When the test was re-run with the final survey data, the difference ($\bar{x}_0$=85.9, $\bar{x}_1$=81.7) was less significant (*p*=0.009).

Surprise results were also indicated when testing the hypothesis that females are less likely than males to enroll in higher-level math course and choose math majors. While 61% of all of the females surveyed were enrolled in either the low or average level math courses (compared to 53% for males) (see Figure 4), 53% of the 28 math majors surveyed were female (see Figure 5). These results were statistically significant at $\alpha=0.10$ as the Chi-square test for GENDER and CLASS had a p-value of 0.063 and the Chi-square test for MAJOR and GENDER had a p-value of 0.057.

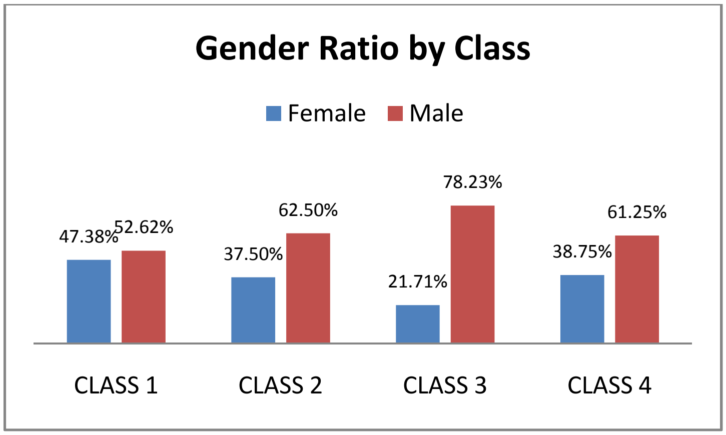


Figure 4 – Gender Ratio by Class

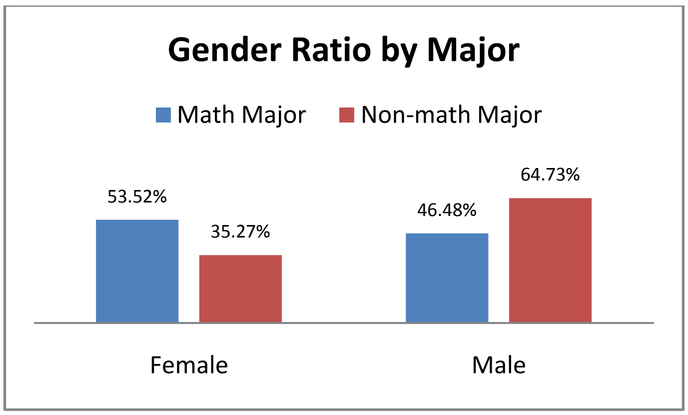


Figure 5 – Gender Ratio by Major

The stepwise regression run for the initial survey data indicated that the two most significant predictors for determining TEST were MSE ($t=4.84$, $p=0.000$) and whether or not the student went to ACE ($t=-3.58$, $p=0.000$). The resulting model was TEST=61.25+6.0MSE-6.8GO TO ACE. Unfortunately, this was not a very good predictive model, as $R^2=15.84$.

A better model was created using the final survey data. The stepwise regression run for the final surveys indicated that four of the tested variables were significant predictors for determining TEST: MSE (t=6.90, p=0.000), GENDER (t=-2.24, p=0.026), GO TO ACE (t=-2.60, p=0.010), and STUDY (t=2.17, p=0.031). The resulting model was TEST=59.09+7.6MSE-2.9GENDER-3.8GO TO ACE+0.46STUDY. With the addition of the GENDER and STUDY variables, the R^2 increased to 23.89. It is interesting to note the sign on gender in this second stepwise, which suggested that test scores are lower for male students than female students. This negative relationship was supported by a t-test comparing the mean test scores reported on the final surveys for males and females. Although the p-value of 0.687 was not significant, there was a difference between the means of the test scores of the female and male students ($\bar{x}_0$=84.9, $\bar{x}_1$=84.1) indicated in the final surveys, and, surprisingly, females, on average, had higher test scores this second time.

DISCUSSION

In running the models for this study, some limitations became apparent immediately. A larger sample size that included all sections of the freshman-level courses at Bryant would have given more weight to any findings of this study. In addition, unfortunately, the question as to whether or not one-on-one instruction from either the professor or tutoring center services can counter the negative effects of low math self-efficacy and high math anxiety cannot be answered at this time. Due to flaws in the survey design, it was impossible to match the initial and final survey results for individual students without drastically decreasing the usable sample size. This was due to the fact that students were allowed to choose whether to use the last four digits of their Bryant ID or social security number as their unique identifier. Unfortunately, the majority of students did not remember which identifier they used in the first survey when taking the second survey, so matched longitudinal analysis could not be conducted. In addition, it was already expected that, with only seven weeks between the initial and final survey administrations, their results would prove very similar and the study would lack a true longitudinal nature. Despite these limitations, much data was usable for analysis of the other hypotheses not dependent on longitudinal data. An independent t-test indicated that the average test score for those who did seek one-on-one instruction improved more than the average test score for those who did not seek one-on-one instruction.

Results of tests of math anxiety and math self-efficacy were in agreement with those of previous studies. In agreement with Betz's (1978) two key findings: students with lower levels of math ability reported higher math anxiety than those in the higher-level math courses, and female students reported higher levels of math anxiety than male students. This study also confirmed Jain and Dowson's (2009) finding that math anxiety and math self-efficacy are negatively correlated. Reflecting both Jain and Dowson's and Betz's findings, students with lower levels of math ability reported lower levels of math self-efficacy than students in higher-level math courses, and female students reported lower levels of math self-efficacy than male students. Like Betz (1978), this study found that math anxiety is negatively correlated with test score; like in the studies of Hoffman (2010) and Pajares and Miller (1994), math self-efficacy was found to be positively correlated with test score. Additionally, in agreement with May and Glynn's (2008) research, the hypothesis that students with higher levels of math anxiety will seek one-on-one help from their professors and/or the University tutoring center staff was found to be true with higher levels of math anxiety reported by those students who saw their professors or went to ACE prior to their exam.

It is interesting to note, however, that few students utilized their professors' office hours at all, and, those who did, were more often female than male (which can be explained by the hypotheses that females have higher math anxiety than males, and that this higher level of math anxiety drives them to seek the help of their professors). The significant, positive correlations between math anxiety and hours spent studying and math anxiety and utilization of ACE services, contrasted nicely with the negative correlations between math self-efficacy and hours spent studying and math self-efficacy and utilization of ACE services, reinforcing the negative correlation between math anxiety and math self-efficacy.

The results of the correlations between hours spent studying and test scores and hours spent at ACE and test scores were surprising. Both correlations were expected to be positive, but the results of this study indicate negative relationships, instead. One possible explanation for this, would be that those students who studied the most and who spend the most time at ACE did so because they were struggling the most with the material and, by studying and going to ACE, they were earning higher grades than they would otherwise receive. This is an example of an instance when it would have been beneficial to have longitudinal data that would enable the determination of the effect the studying and tutoring had on the grades of those students who studied the most and sought the most help at ACE. Previous studies by Cooper (2010) showed that the use of tutoring center services had a significant effect on GPA, but not within a single, semester-long course. Perhaps, it takes longer than one semester to realize such positive results at Bryant as well.

Surprising results were also received for the calculus students. The calculus class had a significantly lower average test score than the other three classes. An explanation for this trend can be found in the way this particular class is filled. All math and actuarial majors at Bryant University are enrolled into calculus their first semester at the school, regardless of their math ability as determined by their math placement test. Occasionally, this results in students with average or lower math ability being in the same class as the highest-level math students. If this was the case this past semester at Bryant, these results can be easily explained. Interestingly, while most females were in the low- and average-level math courses, the majority of the math majors were female. This suggested that female students' higher levels of math anxiety were potentially outweighing their math ability. In general, it can be expected that calculus students tend to care more about their math grades (either because they are concerned about their major GPAs or because they like the subject), than do non-calculus students. Calculus is also the most-challenging freshmen-level math course offered at Bryant. This would explain why calculus students studied and used their professors' office hours at significantly greater levels than the non-calculus students. It is interesting to note, however, that the lowest-level math students spent more hours at ACE than students from any of the other courses, including calculus. As a tutor at ACE, the author of this study knows that the most likely cause of this trend is the fact that the lowest-level math students are particularly targeted by the tutoring center as potential clients.

The results of the stepwise regressions illustrated the problem with the negative correlation between going to ACE at all and test score. In the initial survey case, both math self-efficacy and going to ACE were highly significant predictors of test score. The negative coefficient associated with going to ACE was misleading as it indicated a negative impact of utilization of tutoring center services on test scores, which, logically, does not make sense. Even when the second stepwise was provided for the final survey, it had a negative coefficient for going to ACE. Math self-efficacy was as significant in this second model as it was in the first, but utilization of ACE was less so. In addition, this second model indicated the positive effects of studying on test score (explained by the positive, though insignificant, correlation between test score and study hours reported in this second survey). What was perhaps most important to note about this second regression, however, was the negative coefficient for gender, which implied that by the end of the semester, there had been a shift in the grade distribution by gender, and females were reporting higher grades than males. If these females were the same students who were now seeing positive results on their scores from studying, the encouragement of their spending more time studying for math exams will prove academically rewarding. It may also be that gender came into the equation only through the intervening variable MSE (Center for Positive Practices, 2005). With such small R^2 values, however, these stepwise models must be used with caution. There are some factors not considered by this study that must be significant predictors of test score.

While the individual hypotheses of this study were all tested successfully, the ultimate objective of determining whether the positive effects of getting one-on-one instruction prior to a math exam are able to outweigh the negative effects of low math self-efficacy and high math anxiety could not be verified with certainty. The reason for this was that, in contrast to the assumptions made prior to the study, the correlations between both forms of instruction and test scores were negative. While a likely explanation for this contradiction is that the students who go for extra help are those who need it the most and who would receive lower test score if they did not get that one-on-one attention, the assumption that instruction has a positive effect on test scores remains unsupported. It is interesting to note, however, that the difference between the average test scores of those who utilized some form of one-on-one instruction and those who did not was less significant for the final survey data than the initial survey data. In addition, while there was a 3.1-point increase (p=0.016) in average test score for those who did not use ACE services and/or go to see their professors, there was a 5.9-point increase (p=0.012) in average test score for those who did use the services and/or professors' office hours. This, hopefully, indicates a positive trend that will continue into future semesters as Cooper found in his 2005 study. The sample sizes of these independent t-tests suggested that the students who utilized one-on-one instruction were more likely to be attending class regularly because the same number of students reported using the instruction even when the overall sample size drastically decreased from the administration of the first survey to the second. What could be concluded from this study, however, was that not enough students utilize their professors' office hours or the University's tutoring center services to show a positive relationship between instruction and test scores within a single semester.

APPENDICES

Appendix A – (MINITAB Output for Initial Survey Analysis)

Descriptive Statistics: Gender, Major, Career, Saw Prof, Go to ACE, Instruct (y/n)

```
Gender
N0=107
N1=180
N*=0

Major
N0=258
N1=28
N*=1

Career
N0=197
N1=80
N*=0

Saw Prof
N0=233
N1=53
N*=1

Go to ACE
N0=216
N1=71
N*=0

Instruct (y/n)
N0=199
N1=88
N*=0
```

Descriptive Statistics: MA(Avg), MSE(Avg), Test Score, Study Hours, Prof Hours, ACE Hours, Instruct Hours

Variable	Total Count	N	N*	Mean	StDev	Variance
MA(Avg)	287	287	0	2.5983	0.7686	0.5908
MSE(Avg)	287	287	0	3.5017	0.6507	0.4235
Test Score	287	272	15	80.748	13.930	194.033
Study Hours	287	279	8	2.748	3.822	14.608
Prof Hours	287	281	6	0.3126	1.1471	1.3158
ACE Hours	287	280	7	0.798	2.860	8.180
Instruct Hours	287	287	0	1.085	3.124	9.761

One-way ANOVA: MA(Avg) versus Class

Source	DF	SS	MS	F	P
Class	3	23.221	7.740	15.03	0.000
Error	283	145.748	0.515		
Total	286	168.969			

S = 0.7176   R-Sq = 13.74%   R-Sq(adj) = 12.83%

```
                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level    N    Mean   StDev   -+---------+---------+---------+--------
1       57  3.0193  0.8052                            (------*-----)
2      104  2.7192  0.7520                    (----*---)
3       46  2.4239  0.6614        (------*------)
4       80  2.2413  0.6316   (-----*----)
                             -+---------+---------+---------+--------
                            2.10      2.40      2.70      3.00
```

Pooled StDev = 0.7176

One-way ANOVA: MSE(Avg) versus Class

Source	DF	SS	MS	F	P
Class	3	16.925	5.642	15.32	0.000
Error	283	104.185	0.368		
Total	286	121.109			

S = 0.6067   R-Sq = 13.97%   R-Sq(adj) = 13.06%

```
                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level    N    Mean   StDev   -+---------+---------+---------+--------
1       57  3.1298  0.6563   (-----*------)
2      104  3.4019  0.6309               (----*----)
3       46  3.7174  0.5035                          (------*------)
4       80  3.7725  0.5917                              (----*----)
                             -+---------+---------+---------+--------
                            3.00      3.25      3.50      3.75
```

Pooled StDev = 0.6067

One-way ANOVA: Test Score versus Class

```
Source        DF     SS    MS     F      P
Class          3   5249  1750  9.91  0.000
Error        268  47334   177
Total        271  52583

S = 13.29   R-Sq = 9.98%   R-Sq(adj) = 8.97%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  --------+---------+---------+---------+-
1      54  81.46  11.78               (------*------)
2      96  84.81  10.38                       (-----*----)
3      43  82.90   9.04                 (-------*-------)
4      79  74.15  18.36  (-----*-----)
                         --------+---------+---------+---------+-
                              75.0      80.0      85.0      90.0

Pooled StDev = 13.29
```

One-way ANOVA: Study Hours versus Class

```
Source        DF      SS    MS     F      P
Class          3   257.7  85.9  6.21  0.000
Error        275  3803.2  13.8
Total        278  4060.9

S = 3.719   R-Sq = 6.35%   R-Sq(adj) = 5.32%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level    N   Mean  StDev  ---------+---------+---------+---------+
1       53  2.849  4.763         (---------*----------)
2      102  1.845  2.439  (------*-------)
3       44  2.159  1.256  (----------*----------)
4       80  4.156  4.974                       (--------*-------)
                          ---------+---------+---------+---------+
                                 2.0       3.0       4.0       5.0

Pooled StDev = 3.719
```

One-way ANOVA: Prof Hours versus Class

```
Source        DF      SS    MS     F      P
Class          3   16.04  5.35  4.20  0.006
Error        277  352.38  1.27
Total        280  368.42

S = 1.128   R-Sq = 4.35%   R-Sq(adj) = 3.32%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level    N   Mean  StDev  -------+---------+---------+---------+--
1       55  0.383  0.864            (---------*---------)
2      104  0.103  0.469     (------*-------)
3       46  0.120  0.319  (----------*----------)
4       76  0.666  1.949                       (-------*--------)
                          -------+---------+---------+---------+--
                               0.00      0.30      0.60      0.90

Pooled StDev = 1.128
```

One-way ANOVA: ACE Hours versus Class

```
Source        DF       SS     MS     F      P
Class          3    76.25  25.42  3.18  0.024
Error        276  2206.10   7.99
Total        279  2282.35

S = 2.827   R-Sq = 3.34%   R-Sq(adj) = 2.29%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level    N   Mean  StDev  --------+---------+---------+---------+-
1       54  1.546  4.973                   (--------*---------)
2      101  0.376  1.112        (------*------)
3       46  0.196  0.619  (---------*----------)
4       79  1.177  3.110                (-------*-------)
                          --------+---------+---------+---------+-
                                0.00      0.80      1.60      2.40

Pooled StDev = 2.827
```

One-way ANOVA: Instruct Hours versus Class

Source	DF	SS	MS	F	P
Class	3	139.19	46.40	4.95	0.002
Error	283	2652.54	9.37		
Total	286	2791.73			

S = 3.062   R-Sq = 4.99%   R-Sq(adj) = 3.98%

```
                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level    N   Mean  StDev  ------+---------+---------+---------+---
1       57  1.835  5.033                  (-------*-------)
2      104  0.468  1.305       (-----*-----)
3       46  0.315  0.812  (--------*--------)
4       80  1.795  3.609                   (------*------)
                          ------+---------+---------+---------+---
                              0.0       1.0       2.0       3.0
```

Pooled StDev = 3.062

Two-Sample T-Test and CI: MA(Avg), Gender

Two-sample T for MA(Avg)

Gender	N	Mean	StDev	SE Mean
0	107	2.735	0.860	0.083
1	180	2.517	0.699	0.052

Difference = mu (0) - mu (1)
Estimate for difference: 0.2174
95% lower bound for difference: 0.0637
T-Test of difference = 0 (vs >): T-Value = 2.33 P-Value = 0.010 DF = 285
Both use Pooled StDev = 0.7627

Two-Sample T-Test and CI: MSE(Avg), Gender

Two-sample T for MSE(Avg)

Gender	N	Mean	StDev	SE Mean
0	107	3.378	0.707	0.068
1	180	3.576	0.605	0.045

Difference = mu (0) - mu (1)
Estimate for difference: -0.1980
95% upper bound for difference: -0.0681
T-Test of difference = 0 (vs <): T-Value = -2.52 P-Value = 0.006 DF = 285
Both use Pooled StDev = 0.6448

Two-Sample T-Test and CI: Test Score, Gender

```
Two-sample T for Test Score

Gender    N  Mean  StDev  SE Mean
0       102  80.0   14.7      1.5
1       170  81.2   13.5      1.0


Difference = mu (0) - mu (1)
Estimate for difference:  -1.23
95% upper bound for difference:  1.65
T-Test of difference = 0 (vs <): T-Value = -0.70  P-Value = 0.241  DF = 270
Both use Pooled StDev = 13.9426
```

Two-Sample T-Test and CI: Study Hours, Gender

```
Two-sample T for Study Hours

Gender    N  Mean  StDev  SE Mean
0       103  2.86   3.66     0.36
1       176  2.68   3.92     0.30


Difference = mu (0) - mu (1)
Estimate for difference:  0.180
95% lower bound for difference:  -0.603
T-Test of difference = 0 (vs >): T-Value = 0.38  P-Value = 0.352  DF = 277
Both use Pooled StDev = 3.8279
```

Two-Sample T-Test and CI: Prof Hours, Gender

```
Two-sample T for Prof Hours

Gender    N   Mean  StDev  SE Mean
0       103   0.47   1.64     0.16
1       178  0.220  0.709    0.053


Difference = mu (0) - mu (1)
Estimate for difference:  0.253
95% lower bound for difference:  0.019
T-Test of difference = 0 (vs >): T-Value = 1.79  P-Value = 0.038  DF = 279
Both use Pooled StDev = 1.1426
```

Two-Sample T-Test and CI: ACE Hours, Gender

```
Two-sample T for ACE Hours

Gender    N  Mean  StDev  SE Mean
0       101  0.77   2.46     0.24
1       179  0.82   3.07     0.23


Difference = mu (0) - mu (1)
Estimate for difference:  -0.048
95% lower bound for difference:  -0.637
T-Test of difference = 0 (vs >): T-Value = -0.14  P-Value = 0.554  DF = 278
Both use Pooled StDev = 2.8652
```

Two-Sample T-Test and CI: Instruct Hours, Gender

```
Two-sample T for Instruct Hours

Gender    N  Mean  StDev  SE Mean
0       107  1.18   2.95     0.28
1       180  1.03   3.23     0.24


Difference = mu (0) - mu (1)
Estimate for difference:  0.150
95% lower bound for difference:  -0.480
T-Test of difference = 0 (vs >): T-Value = 0.39  P-Value = 0.347  DF = 285
Both use Pooled StDev = 3.1289
```

Two-Sample T-Test and CI: Test Score, Saw Prof

```
Two-sample T for Test Score

Saw
Prof    N  Mean  StDev  SE Mean
0     223  81.4   13.6     0.91
1      48  78.8   14.1      2.0


Difference = mu (0) - mu (1)
Estimate for difference:  2.54
95% upper bound for difference:  6.12
T-Test of difference = 0 (vs <): T-Value = 1.17  P-Value = 0.878  DF = 269
Both use Pooled StDev = 13.6520
```

Two-Sample T-Test and CI: Test Score, Go to ACE

```
Two-sample T for Test Score

Go to
ACE      N  Mean  StDev  SE Mean
0      209  82.9   11.7     0.81
1       63  73.7   18.0      2.3


Difference = mu (0) - mu (1)
Estimate for difference:  9.20
95% upper bound for difference:  12.37
T-Test of difference = 0 (vs <): T-Value = 4.77  P-Value = 1.000  DF = 270
Both use Pooled StDev = 13.4012
```

Two-Sample T-Test and CI: Test Score, Instruct (y/n)

```
Two-sample T for Test Score

Instruct
(y/n)       N  Mean  StDev  SE Mean
0         191  82.8   11.6     0.84
1          81  75.8   17.5      1.9


Difference = mu (0) - mu (1)
Estimate for difference:  6.99
95% upper bound for difference:  9.96
T-Test of difference = 0 (vs <): T-Value = 3.88  P-Value = 1.000  DF = 270
Both use Pooled StDev = 13.5815
```

Two-Sample T-Test and CI: MA(Avg), Saw Prof

```
Two-sample T for MA(Avg)

Saw
Prof    N   Mean  StDev  SE Mean
0     233  2.564  0.765    0.050
1      53  2.742  0.778     0.11


Difference = mu (0) - mu (1)
Estimate for difference:  -0.178
95% upper bound for difference:  0.015
T-Test of difference = 0 (vs <): T-Value = -1.52  P-Value = 0.065  DF = 284
Both use Pooled StDev = 0.7679
```

Two-Sample T-Test and CI: MA(Avg), Go to ACE

```
Two-sample T for MA(Avg)

Go to
ACE      N   Mean  StDev  SE Mean
0      216  2.458  0.727    0.049
1       71  3.024  0.738    0.088


Difference = mu (0) - mu (1)
Estimate for difference:  -0.5656
95% upper bound for difference:  -0.4008
T-Test of difference = 0 (vs <): T-Value = -5.66  P-Value = 0.000  DF = 285
Both use Pooled StDev = 0.7300
```

Two-Sample T-Test and CI: MA(Avg), Instruct (y/n)

```
Two-sample T for MA(Avg)

Instruct
(y/n)       N   Mean  StDev  SE Mean
0         199  2.489  0.756    0.054
1          88  2.844  0.743    0.079


Difference = mu (0) - mu (1)
Estimate for difference:  -0.3549
95% upper bound for difference:  -0.1959
T-Test of difference = 0 (vs <): T-Value = -3.68  P-Value = 0.000  DF = 285
Both use Pooled StDev = 0.7523
```

Two-Sample T-Test and CI: Test Score, Instruct (y/n)

```
Two-sample T for Test Score

Instruct
(y/n)       N  Mean  StDev  SE Mean
0         191  82.8   11.6     0.84
1          81  75.8   17.5      1.9


Difference = mu (0) - mu (1)
Estimate for difference:  6.99
95% CI for difference:  (3.44, 10.54)
T-Test of difference = 0 (vs not =): T-Value = 3.88  P-Value = 0.000  DF = 270
Both use Pooled StDev = 13.5815
```

Correlations: MA(Avg), MSE(Avg)

```
Pearson correlation of MA(Avg) and MSE(Avg) = -0.768
P-Value = 0.000
```

Correlations: MA(Avg), Test Score

```
Pearson correlation of MA(Avg) and Test Score = -0.280
P-Value = 0.000
```

Correlations: MA(Avg), Study Hours

```
Pearson correlation of MA(Avg) and Study Hours = 0.135
P-Value = 0.024
```

Correlations: MA(Avg), Prof Hours

```
Pearson correlation of MA(Avg) and Prof Hours = 0.085
P-Value = 0.153
```

Correlations: MA(Avg), ACE Hours

```
Pearson correlation of MA(Avg) and ACE Hours = 0.193
P-Value = 0.001
```

Correlations: MA(Avg), Instruct Hours

```
Pearson correlation of MA(Avg) and Instruct Hours = 0.195
P-Value = 0.001
```

Correlations: MSE(Avg), Test Score

```
Pearson correlation of MSE(Avg) and Test Score = 0.336
P-Value = 0.000
```

Correlations: MSE(Avg), Study Hours

```
Pearson correlation of MSE(Avg) and Study Hours = -0.099
P-Value = 0.098
```

Correlations: MSE(Avg), Prof Hours

```
Pearson correlation of MSE(Avg) and Prof Hours = -0.066
P-Value = 0.267
```

Correlations: MSE(Avg), ACE Hours

```
Pearson correlation of MSE(Avg) and ACE Hours = -0.140
P-Value = 0.019
```

Correlations: MSE(Avg), Instruct Hours

```
Pearson correlation of MSE(Avg) and Instruct Hours = -0.142
P-Value = 0.016
```

Correlations: Study Hours, Test Score

```
Pearson correlation of Study Hours and Test Score = -0.110
P-Value = 0.072
```

Correlations: Prof Hours, Test Score

```
Pearson correlation of Prof Hours and Test Score = -0.085
P-Value = 0.167
```

Correlations: ACE Hours, Test Score

```
Pearson correlation of ACE Hours and Test Score = -0.157
P-Value = 0.010
```

Correlations: Instruct Hours, Test Score

```
Pearson correlation of Instruct Hours and Test Score = -0.168
P-Value = 0.006
```

Tabulated statistics: Gender, Class

Rows: Gender   Columns: Class

	1	2	3	4	All
0	27	39	10	31	107
	9.41	13.59	3.48	10.80	37.28
1	30	65	36	49	180
	10.45	22.65	12.54	17.07	62.72
All	57	104	46	80	287
	19.86	36.24	16.03	27.87	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 7.308, DF = 3, P-Value = 0.063
Likelihood Ratio Chi-Square = 7.638, DF = 3, P-Value = 0.054

Tabulated statistics: Career, Class

Rows: Career   Columns: Class

	1	2	3	4	All
0	47	83	36	31	197
	16.97	29.96	13.00	11.19	71.12
1	9	19	9	43	80
	3.25	6.86	3.25	15.52	28.88
Missing	1	2	1	6	*
	*	*	*	*	*
All	56	102	45	74	277
	20.22	36.82	16.25	26.71	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 42.198, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 39.878, DF = 3, P-Value = 0.000

Tabulated statistics: Saw Prof, Class

Rows: Saw Prof   Columns: Class

	1	2	3	4	All
0	41	97	40	55	233
	14.34	33.92	13.99	19.23	81.47
1	16	7	6	24	53
	5.59	2.45	2.10	8.39	18.53
Missing	0	0	0	1	*
	*	*	*	*	*
All	57	104	46	79	286
	19.93	36.36	16.08	27.62	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 21.292, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 22.581, DF = 3, P-Value = 0.000

Tabulated statistics: Go to ACE, Class

Rows: Go to ACE   Columns: Class

	1	2	3	4	All
0	34	85	41	56	216
	11.85	29.62	14.29	19.51	75.26
1	23	19	5	24	71
	8.01	6.62	1.74	8.36	24.74
All	57	104	46	80	287
	19.86	36.24	16.03	27.87	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 15.742, DF = 3, P-Value = 0.001
Likelihood Ratio Chi-Square = 15.979, DF = 3, P-Value = 0.001

Tabulated statistics: Instruct (y/n), Class

Rows: Instruct (y/n)   Columns: Class

	1	2	3	4	All
0	33	85	37	44	199
	11.50	29.62	12.89	15.33	69.34
1	24	19	9	36	88
	8.36	6.62	3.14	12.54	30.66
All	57	104	46	80	287
	19.86	36.24	16.03	27.87	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 21.423, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 21.731, DF = 3, P-Value = 0.000

Tabulated statistics: Major, Gender

Rows: Major   Columns: Gender

	0	1	All
0	91	167	258
	31.82	58.39	90.21
1	15	13	28
	5.24	4.55	9.79
Missing	1	0	*
	*	*	*
All	106	180	286
	37.06	62.94	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 3.626, DF = 1, P-Value = 0.057
Likelihood Ratio Chi-Square = 3.500, DF = 1, P-Value = 0.061

Tabulated statistics: Career, Gender

Rows: Career   Columns: Gender

	0	1	All
0	67	130	197
	24.19	46.93	71.12
1	35	45	80
	12.64	16.25	28.88
Missing	5	5	*
	*	*	*
All	102	175	277
	36.82	63.18	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 2.320, DF = 1, P-Value = 0.128
Likelihood Ratio Chi-Square = 2.291, DF = 1, P-Value = 0.130

Tabulated statistics: Saw Prof, Gender

Rows: Saw Prof   Columns: Gender

	0	1	All
0	81	152	233
	28.32	53.15	81.47
1	25	28	53
	8.74	9.79	18.53
Missing	1	0	*
	*	*	*
All	106	180	286
	37.06	62.94	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 2.849, DF = 1, P-Value = 0.091
Likelihood Ratio Chi-Square = 2.787, DF = 1, P-Value = 0.095

Tabulated statistics: Go to ACE, Gender

Rows: Go to ACE   Columns: Gender

	0	1	All
0	80	136	216
	27.87	47.39	75.26
1	27	44	71
	9.41	15.33	24.74
All	107	180	287
	37.28	62.72	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 0.022, DF = 1, P-Value = 0.881
Likelihood Ratio Chi-Square = 0.022, DF = 1, P-Value = 0.881

Tabulated statistics: Instruct (y/n), Gender

Rows: Instruct (y/n)   Columns: Gender

	0	1	All
0	71	128	199
	24.74	44.60	69.34
1	36	52	88
	12.54	18.12	30.66
All	107	180	287
	37.28	62.72	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 0.714, DF = 1, P-Value = 0.398
Likelihood Ratio Chi-Square = 0.709, DF = 1, P-Value = 0.400

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Saw Prof, Go to ACE

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 6 predictors, with N = 268
N(cases with missing observations) = 19 N(all cases) = 287


Step            1      2
Constant    55.30  61.25

MSE(Avg)      7.2    6.0
T-Value      5.96   4.84
P-Value     0.000  0.000

Go to ACE           -6.8
T-Value            -3.58
P-Value            0.000

S            12.9   12.6
R-Sq        11.77  15.84
R-Sq(adj)   11.44  15.21
Mallows Cp   10.9    0.2
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Prof Hours, ACE Hours

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 6 predictors, with N = 259
N(cases with missing observations) = 28 N(all cases) = 287


Step            1      2
Constant    54.58  56.01

MSE(Avg)      7.5    7.2
T-Value      5.97   5.70
P-Value     0.000  0.000

ACE Hours          -0.50
T-Value            -1.76
P-Value            0.079

S            12.9   12.8
R-Sq        12.17  13.22
R-Sq(adj)   11.83  12.55
Mallows Cp    2.8    1.8
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Instruct (y/n)

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 5 predictors, with N = 269
N(cases with missing observations) = 18 N(all cases) = 287


Step                1      2
Constant        54.43  58.73

MSE(Avg)          7.4    6.6
T-Value          6.02   5.31
P-Value         0.000  0.000

Instruct (y/n)          -5.1
T-Value                -2.87
P-Value                0.004

S                13.1   12.9
R-Sq            11.94  14.60
R-Sq(adj)       11.61  13.95
Mallows Cp        7.3    1.1
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Instruct Hours

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 5 predictors, with N = 269
N(cases with missing observations) = 18 N(all cases) = 287


Step              1      2
Constant      54.43  56.24

MSE(Avg)        7.4    7.1
T-Value        6.02   5.72
P-Value       0.000  0.000

Instruct Hours       -0.55
T-Value              -2.15
P-Value              0.032

S              13.1   13.0
R-Sq          11.94  13.45
R-Sq(adj)     11.61  12.80
Mallows Cp      3.6    1.0
```

Appendix B – (MINITAB Output for Final Survey Analysis)

Descriptive Statistics: Gender, Major, Career, Saw Prof, Go to ACE, Instruct (y/n)

```
Gender
N0=83
N1=146
N*=0

Major
N0=204
N1=25
N*=0

Career
N0=151
N1=77
N*=1

Saw Prof
N0=184
N1=45
N*=0

Go to ACE
N0=163
N1=66
N*=0

Instruct (y/n)
N0=147
N1=82
N*=0
```

Descriptive Statistics: MA(Avg), MSE(Avg), Test Score, Study Hours, Prof Hours, ACE Hours, Instruct Hours

Variable	Total Count	N	N*	Mean	StDev	Variance
MA(Avg)	229	229	0	2.5445	0.7366	0.5426
MSE(Avg)	229	229	0	3.5930	0.6014	0.3617
Test Score	229	224	5	84.406	11.556	133.534
Study Hours	229	226	3	3.011	3.005	9.029
Prof Hours	229	225	4	0.3878	1.1863	1.4073
ACE Hours	229	223	6	1.142	3.043	9.257
Instruct Hours	229	229	0	1.493	3.308	10.942

One-way ANOVA: MA(Avg) versus Class

```
Source        DF       SS     MS      F      P
Class          3   21.409  7.136  15.70  0.000
Error        225  102.296  0.455
Total        228  123.706

S = 0.6743   R-Sq = 17.31%   R-Sq(adj) = 16.20%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level   N    Mean   StDev  ----+---------+---------+---------+-----
1      38  3.0053  0.6873                         (-----*-----)
2      82  2.7073  0.7476                  (---*----)
3      44  2.4432  0.6652         (-----*-----)
4      65  2.1385  0.5662  (----*----)
                           ----+---------+---------+---------+-----
                             2.10      2.45      2.80      3.15

Pooled StDev = 0.6743
```

One-way ANOVA: MSE(Avg) versus Class

```
Source        DF      SS     MS     F      P
Class          3   9.183  3.061  9.40  0.000
Error        225  73.286  0.326
Total        228  82.469

S = 0.5707   R-Sq = 11.13%   R-Sq(adj) = 9.95%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level   N    Mean   StDev  ----+---------+---------+---------+-----
1      38  3.3421  0.5712  (-------*------)
2      82  3.4415  0.6361         (----*----)
3      44  3.7136  0.4925                (------*-----)
4      65  3.8492  0.5304                      (-----*-----)
                           ----+---------+---------+---------+-----
                             3.25      3.50      3.75      4.00

Pooled StDev = 0.5707
```

One-way ANOVA: Test Score versus Class

```
Source         DF     SS   MS     F       P
Class           3    453  151  1.13  0.337
Error         220  29325  133
Total         223  29778

S = 11.55   R-Sq = 1.52%   R-Sq(adj) = 0.18%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  --------+---------+---------+---------+-
1      36  83.19   9.96     (-----------*------------)
2      80  85.11  13.92             (--------*-------)
3      43  82.05  10.04  (----------*-----------)
4      65  85.77   9.92              (---------*--------)
                         --------+---------+---------+---------+-
                              81.0      84.0      87.0      90.0

Pooled StDev = 11.55
```

One-way ANOVA: Study Hours versus Class

```
Source         DF       SS     MS     F      P
Class           3   211.16  70.39  8.58  0.000
Error         222  1820.35   8.20
Total         225  2031.51

S = 2.864   R-Sq = 10.39%   R-Sq(adj) = 9.18%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev   -+---------+---------+---------+--------
1      38  1.993  1.824   (-------*------)
2      80  2.564  2.779          (----*-----)
3      43  2.488  1.774        (------*------)
4      65  4.500  3.863                          (-----*----)
                          -+---------+---------+---------+--------
                         1.2       2.4       3.6       4.8

Pooled StDev = 2.864
```

One-way ANOVA: Prof Hours versus Class

Source	DF	SS	MS	F	P
Class	3	25.04	8.35	6.36	0.000
Error	221	290.18	1.31		
Total	224	315.23			

S = 1.146   R-Sq = 7.94%   R-Sq(adj) = 6.70%

```
                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  ------+---------+---------+---------+---
1      37  0.209  0.462    (--------*---------)
2      79  0.203  0.962       (-----*-----)
3      44  0.102  0.367  (--------*-------)
4      65  0.908  1.787                        (------*------)
                         ------+---------+---------+---------+---
                             0.00      0.40      0.80      1.20
```

Pooled StDev = 1.146

One-way ANOVA: ACE Hours versus Class

Source	DF	SS	MS	F	P
Class	3	79.92	26.64	2.95	0.033
Error	219	1975.12	9.02		
Total	222	2055.04			

S = 3.003   R-Sq = 3.89%   R-Sq(adj) = 2.57%

```
                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  ---------+---------+---------+---------+
1      37  1.743  2.862                   (--------*---------)
2      80  1.122  3.285                (-----*------)
3      42  0.000  0.000  (--------*--------)
4      64  1.570  3.625                   (-------*------)
                         ---------+---------+---------+---------+
                                0.0       1.0       2.0       3.0
```

Pooled StDev = 3.003

One-way ANOVA: Instruct Hours versus Class

Source	DF	SS	MS	F	P
Class	3	154.8	51.6	4.96	0.002
Error	225	2340.0	10.4		
Total	228	2494.9			

S = 3.225   R-Sq = 6.21%   R-Sq(adj) = 4.96%

```
                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  -------+---------+---------+---------+--
1      38  1.901  2.848                (--------*-------)
2      82  1.290  3.436              (-----*-----)
3      44  0.102  0.367  (-------*-------)
4      65  2.454  4.104                     (-----*------)
                         -------+---------+---------+---------+--
                              0.0       1.2       2.4       3.6
```

Pooled StDev = 3.225

Two-Sample T-Test and CI: MA(Avg), Gender

Two-sample T for MA(Avg)

Gender	N	Mean	StDev	SE Mean
0	83	2.640	0.759	0.083
1	146	2.490	0.721	0.060

```
Difference = mu (0) - mu (1)
Estimate for difference:  0.149
95% lower bound for difference:  -0.017
T-Test of difference = 0 (vs >): T-Value = 1.48  P-Value = 0.070  DF = 227
Both use Pooled StDev = 0.7347
```

Two-Sample T-Test and CI: MSE(Avg), Gender

Two-sample T for MSE(Avg)

Gender	N	Mean	StDev	SE Mean
0	83	3.489	0.635	0.070
1	146	3.652	0.575	0.048

```
Difference = mu (0) - mu (1)
Estimate for difference:  -0.1629
95% upper bound for difference:  -0.0272
T-Test of difference = 0 (vs <): T-Value = -1.98  P-Value = 0.024  DF = 227
Both use Pooled StDev = 0.5976
```

Two-Sample T-Test and CI: Test Score, Gender

```
Two-sample T for Test Score

Gender    N  Mean  StDev  SE Mean
0        79  84.9   13.8      1.5
1       145  84.1   10.2     0.85


Difference = mu (0) - mu (1)
Estimate for difference:  0.79
95% upper bound for difference:  3.46
T-Test of difference = 0 (vs <): T-Value = 0.49  P-Value = 0.687  DF = 222
Both use Pooled StDev = 11.5755
```

Two-Sample T-Test and CI: Study Hours, Gender

```
Two-sample T for Study Hours

Gender    N  Mean  StDev  SE Mean
0        81  3.21   2.70     0.30
1       145  2.90   3.17     0.26


Difference = mu (0) - mu (1)
Estimate for difference:  0.315
95% lower bound for difference:  -0.374
T-Test of difference = 0 (vs >): T-Value = 0.76  P-Value = 0.225  DF = 224
Both use Pooled StDev = 3.0077
```

Two-Sample T-Test and CI: Prof Hours, Gender

```
Two-sample T for Prof Hours

Gender    N  Mean  StDev  SE Mean
0        80  0.43   1.22     0.14
1       145  0.36   1.17    0.097


Difference = mu (0) - mu (1)
Estimate for difference:  0.067
95% lower bound for difference:  -0.206
T-Test of difference = 0 (vs >): T-Value = 0.41  P-Value = 0.342  DF = 223
Both use Pooled StDev = 1.1885
```

Two-Sample T-Test and CI: ACE Hours, Gender

```
Two-sample T for ACE Hours

Gender    N  Mean  StDev  SE Mean
0        81  1.08   2.19     0.24
1       142  1.18   3.44     0.29


Difference = mu (0) - mu (1)
Estimate for difference:  -0.093
95% lower bound for difference:  -0.794
T-Test of difference = 0 (vs >): T-Value = -0.22  P-Value = 0.586  DF = 221
Both use Pooled StDev = 3.0491
```

Two-Sample T-Test and CI: Instruct Hours, Gender

```
Two-sample T for Instruct Hours

Gender    N  Mean  StDev  SE Mean
0        83  1.47   2.55     0.28
1       146  1.51   3.68     0.30


Difference = mu (0) - mu (1)
Estimate for difference:  -0.032
95% lower bound for difference:  -0.785
T-Test of difference = 0 (vs >): T-Value = -0.07  P-Value = 0.528  DF = 227
Both use Pooled StDev = 3.3152
```

Two-Sample T-Test and CI: Test Score, Saw Prof

```
Two-sample T for Test Score

Saw
Prof    N  Mean  StDev  SE Mean
0     180  84.5   11.7     0.87
1      44  84.1   11.0      1.7


Difference = mu (0) - mu (1)
Estimate for difference:  0.35
95% upper bound for difference:  3.57
T-Test of difference = 0 (vs <): T-Value = 0.18  P-Value = 0.571  DF = 222
Both use Pooled StDev = 11.5808
```

Two-Sample T-Test and CI: Test Score, Go to ACE

```
Two-sample T for Test Score

Go to
ACE      N  Mean  StDev  SE Mean
0      160  85.8   11.6     0.92
1       64  80.8   10.7      1.3


Difference = mu (0) - mu (1)
Estimate for difference:  5.00
95% upper bound for difference:  7.77
T-Test of difference = 0 (vs <): T-Value = 2.98  P-Value = 0.998  DF = 222
Both use Pooled StDev = 11.3574
```

Two-Sample T-Test and CI: Test Score, Instruct (y/n)

```
Two-sample T for Test Score

Instruct
(y/n)       N  Mean  StDev  SE Mean
0         144  85.9   11.6     0.96
1          80  81.7   11.1      1.2


Difference = mu (0) - mu (1)
Estimate for difference:  4.17
95% upper bound for difference:  6.80
T-Test of difference = 0 (vs <): T-Value = 2.62  P-Value = 0.995  DF = 222
Both use Pooled StDev = 11.4064
```

Two-Sample T-Test and CI: MA(Avg), Saw Prof

```
Two-sample T for MA(Avg)

Saw
Prof    N   Mean  StDev  SE Mean
0     184  2.520  0.742    0.055
1      45  2.644  0.713     0.11


Difference = mu (0) - mu (1)
Estimate for difference:  -0.124
95% upper bound for difference:  0.078
T-Test of difference = 0 (vs <): T-Value = -1.02  P-Value = 0.156  DF = 227
Both use Pooled StDev = 0.7365
```

Two-Sample T-Test and CI: MA(Avg), Go to ACE

```
Two-sample T for MA(Avg)

Go to
ACE      N   Mean  StDev  SE Mean
0      163  2.403  0.702    0.055
1       66  2.894  0.708    0.087


Difference = mu (0) - mu (1)
Estimate for difference:  -0.491
95% upper bound for difference:  -0.321
T-Test of difference = 0 (vs <): T-Value = -4.78  P-Value = 0.000  DF = 227
Both use Pooled StDev = 0.7036
```

Two-Sample T-Test and CI: MA(Avg), Instruct (y/n)

```
Two-sample T for MA(Avg)

Instruct
(y/n)       N   Mean  StDev  SE Mean
0         147  2.414  0.704    0.058
1          82  2.778  0.739    0.082


Difference = mu (0) - mu (1)
Estimate for difference:  -0.3638
95% upper bound for difference:  -0.2005
T-Test of difference = 0 (vs <): T-Value = -3.68  P-Value = 0.000  DF = 227
Both use Pooled StDev = 0.7171
```

Two-Sample T-Test and CI: Test Score, Instruct (y/n)

```
Two-sample T for Test Score

Instruct
(y/n)       N  Mean  StDev  SE Mean
0         144  85.9   11.6     0.96
1          80  81.7   11.1      1.2


Difference = mu (0) - mu (1)
Estimate for difference:  4.17
95% CI for difference:  (1.04, 7.31)
T-Test of difference = 0 (vs not =): T-Value = 2.62  P-Value = 0.009  DF = 222
Both use Pooled StDev = 11.4064
```

Correlations: MA(Avg), MSE(Avg)

```
Pearson correlation of MA(Avg) and MSE(Avg) = -0.736
P-Value = 0.000
```

Correlations: MA(Avg), Test Score

```
Pearson correlation of MA(Avg) and Test Score = -0.251
P-Value = 0.000
```

Correlations: MA(Avg), Study Hours

```
Pearson correlation of MA(Avg) and Study Hours = 0.186
P-Value = 0.005
```

Correlations: MA(Avg), Prof Hours

```
Pearson correlation of MA(Avg) and Prof Hours = 0.057
P-Value = 0.395
```

Correlations: MA(Avg), ACE Hours

```
Pearson correlation of MA(Avg) and ACE Hours = 0.247
P-Value = 0.000
```

Correlations: MA(Avg), Instruct Hours

```
Pearson correlation of MA(Avg) and Instruct Hours = 0.235
P-Value = 0.000
```

Correlations: MSE(Avg), Test Score

```
Pearson correlation of MSE(Avg) and Test Score = 0.382
P-Value = 0.000
```

Correlations: MSE(Avg), Study Hours

```
Pearson correlation of MSE(Avg) and Study Hours = -0.187
P-Value = 0.005
```

Correlations: MSE(Avg), Prof Hours

```
Pearson correlation of MSE(Avg) and Prof Hours = -0.100
P-Value = 0.137
```

Correlations: MSE(Avg), ACE Hours

```
Pearson correlation of MSE(Avg) and ACE Hours = -0.184
P-Value = 0.006
```

Correlations: MSE(Avg), Instruct Hours

```
Pearson correlation of MSE(Avg) and Instruct Hours = -0.199
P-Value = 0.002
```

Correlations: Study Hours, Test Score

```
Pearson correlation of Study Hours and Test Score = 0.023
P-Value = 0.733
```

Correlations: Prof Hours, Test Score

```
Pearson correlation of Prof Hours and Test Score = 0.053
P-Value = 0.435
```

Correlations: ACE Hours, Test Score

```
Pearson correlation of ACE Hours and Test Score = -0.162
P-Value = 0.016
```

Correlations: Instruct Hours, Test Score

```
Pearson correlation of Instruct Hours and Test Score = -0.127
P-Value = 0.058
```

Tabulated statistics: Gender, Class

Rows: Gender   Columns: Class

	1	2	3	4	All
0	17	32	8	26	83
	7.42	13.97	3.49	11.35	36.24
1	21	50	36	39	146
	9.17	21.83	15.72	17.03	63.76
All	38	82	44	65	229
	16.59	35.81	19.21	28.38	100.00

Cell Contents: Count
                    % of Total

Pearson Chi-Square = 8.069, DF = 3, P-Value = 0.045
Likelihood Ratio Chi-Square = 8.738, DF = 3, P-Value = 0.033

Tabulated statistics: Career, Class

Rows: Career   Columns: Class

	1	2	3	4	All
0	30	63	33	25	151
	13.16	27.63	14.47	10.96	66.23
1	8	19	10	40	77
	3.51	8.33	4.39	17.54	33.77
Missing	0	0	1	0	*
	*	*	*	*	*
All	38	82	43	65	228
	16.67	35.96	18.86	28.51	100.00

Cell Contents: Count
                    % of Total

Pearson Chi-Square = 31.401, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 30.467, DF = 3, P-Value = 0.000

Tabulated statistics: Saw Prof, Class

Rows: Saw Prof   Columns: Class

	1	2	3	4	All
0	29	73	40	42	184
	12.66	31.88	17.47	18.34	80.35
1	9	9	4	23	45
	3.93	3.93	1.75	10.04	19.65
All	38	82	44	65	229
	16.59	35.81	19.21	28.38	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 17.599, DF = 3, P-Value = 0.001
Likelihood Ratio Chi-Square = 17.319, DF = 3, P-Value = 0.001

Tabulated statistics: Go to ACE, Class

Rows: Go to ACE   Columns: Class

	1	2	3	4	All
0	18	60	42	43	163
	7.86	26.20	18.34	18.78	71.18
1	20	22	2	22	66
	8.73	9.61	0.87	9.61	28.82
All	38	82	44	65	229
	16.59	35.81	19.21	28.38	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 24.100, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 27.626, DF = 3, P-Value = 0.000

Tabulated statistics: Instruct (y/n), Class

Rows: Instruct (y/n)   Columns: Class

	1	2	3	4	All
0	15	59	40	33	147
	6.55	25.76	17.47	14.41	64.19
1	23	23	4	32	82
	10.04	10.04	1.75	13.97	35.81
All	38	82	44	65	229
	16.59	35.81	19.21	28.38	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 31.007, DF = 3, P-Value = 0.000
Likelihood Ratio Chi-Square = 33.552, DF = 3, P-Value = 0.000

Tabulated statistics: Major, Gender

Rows: Major   Columns: Gender

	0	1	All
0	71	133	204
	31.00	58.08	89.08
1	12	13	25
	5.24	5.68	10.92
All	83	146	229
	36.24	63.76	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 1.678, DF = 1, P-Value = 0.195
Likelihood Ratio Chi-Square = 1.627, DF = 1, P-Value = 0.202

Tabulated statistics: Career, Gender

Rows: Career Columns: Gender

	0	1	All
0	51	100	151
	22.37	43.86	66.23
1	32	45	77
	14.04	19.74	33.77
Missing	0	1	*
	*	*	*
All	83	145	228
	36.40	63.60	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 1.334, DF = 1, P-Value = 0.248
Likelihood Ratio Chi-Square = 1.324, DF = 1, P-Value = 0.250

Tabulated statistics: Saw Prof, Gender

Rows: Saw Prof Columns: Gender

	0	1	All
0	64	120	184
	27.95	52.40	80.35
1	19	26	45
	8.30	11.35	19.65
All	83	146	229
	36.24	63.76	100.00

Cell Contents: Count
% of Total

Pearson Chi-Square = 0.866, DF = 1, P-Value = 0.352
Likelihood Ratio Chi-Square = 0.853, DF = 1, P-Value = 0.356

Tabulated statistics: Go to ACE, Gender

```
Rows: Go to ACE   Columns: Gender

            0      1     All

0          55    108     163
        24.02  47.16   71.18

1          28     38      66
        12.23  16.59   28.82

All        83    146     229
        36.24  63.76  100.00

Cell Contents:      Count
                    % of Total


Pearson Chi-Square = 1.532, DF = 1, P-Value = 0.216
Likelihood Ratio Chi-Square = 1.514, DF = 1, P-Value = 0.219
```

Tabulated statistics: Instruct (y/n), Gender

```
Rows: Instruct (y/n)   Columns: Gender

            0      1     All

0          49     98     147
        21.40  42.79   64.19

1          34     48      82
        14.85  20.96   35.81

All        83    146     229
        36.24  63.76  100.00

Cell Contents:      Count
                    % of Total


Pearson Chi-Square = 1.506, DF = 1, P-Value = 0.220
Likelihood Ratio Chi-Square = 1.495, DF = 1, P-Value = 0.221
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Saw Prof, Go to ACE

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 6 predictors, with N = 222
N(cases with missing observations) = 7 N(all cases) = 229


Step            1      2      3      4
Constant    57.13  58.11  61.34  59.09

MSE(Avg)      7.7    7.9    7.3    7.6
T-Value      7.15   7.40   6.63   6.90
P-Value     0.000  0.000  0.000  0.000

Gender              -2.9   -3.0   -2.9
T-Value            -2.16  -2.27  -2.24
P-Value            0.032  0.024  0.026

Go to ACE                  -3.1   -3.8
T-Value                   -2.18  -2.60
P-Value                   0.030  0.010

Study Hours                       0.46
T-Value                           2.17
P-Value                          0.031

S            9.45   9.37   9.29   9.21
R-Sq        18.86  20.56  22.25  23.89
R-Sq(adj)   18.49  19.83  21.18  22.49
Mallows Cp   12.8   10.0    7.2    4.5
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Prof Hours, ACE Hours

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 6 predictors, with N = 215
N(cases with missing observations) = 14 N(all cases) = 229


Step             1      2      3      4
Constant     55.97  57.77  55.23  56.24

MSE(Avg)       8.0    7.6    7.9    8.1
T-Value       7.29   6.89   7.19   7.35
P-Value      0.000  0.000  0.000  0.000

ACE Hours           -0.42  -0.53  -0.50
T-Value             -1.95  -2.42  -2.33
P-Value             0.052  0.016  0.021

Study Hours                 0.49   0.47
T-Value                     2.25   2.19
P-Value                    0.026  0.030

Gender                             -2.4
T-Value                           -1.80
P-Value                           0.074

S             9.47   9.40   9.32   9.27
R-Sq         19.95  21.36  23.20  24.36
R-Sq(adj)    19.57  20.62  22.11  22.92
Mallows Cp    10.9    9.0    5.9    4.6
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Instruct (y/n)

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 5 predictors, with N = 222
N(cases with missing observations) = 7 N(all cases) = 229


Step                1      2      3      4
Constant        57.13  58.11  55.92  58.96

MSE(Avg)          7.7    7.9    8.2    7.6
T-Value          7.15   7.40   7.60   6.83
P-Value         0.000  0.000  0.000  0.000

Gender                  -2.9   -2.8   -2.9
T-Value                -2.16  -2.13  -2.24
P-Value                0.032  0.035  0.026

Study Hours                    0.35   0.46
T-Value                        1.64   2.13
P-Value                       0.102  0.034

Instruct (y/n)                        -3.0
T-Value                              -2.10
P-Value                              0.037

S                9.45   9.37   9.33   9.26
R-Sq            18.86  20.56  21.53  23.09
R-Sq(adj)       18.49  19.83  20.45  21.67
Mallows Cp       10.4    7.6    6.9    4.5
```

Stepwise Regression: Test Score versus Gender, MA(Avg), MSE(Avg), Study Hours, Instruct Hours

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Test Score on 5 predictors, with N = 222
N(cases with missing observations) = 7 N(all cases) = 229


Step                1      2      3      4
Constant        57.13  58.11  55.92  57.07

MSE(Avg)          7.7    7.9    8.2    7.9
T-Value          7.15   7.40   7.60   7.28
P-Value         0.000  0.000  0.000  0.000

Gender                  -2.9   -2.8   -2.7
T-Value                -2.16  -2.13  -2.07
P-Value                0.032  0.035  0.040

Study Hours                    0.35   0.45
T-Value                        1.64   2.07
P-Value                       0.102  0.040

Instruct Hours                       -0.34
T-Value                              -1.67
P-Value                              0.096

S                9.45   9.37   9.33   9.30
R-Sq            18.86  20.56  21.53  22.53
R-Sq(adj)       18.49  19.83  20.45  21.10
Mallows Cp        9.0    6.2    5.5    4.7
```

Appendix C – (MINITAB Output for Analysis of Utilization of One-on-one Instruction)

Two-Sample T-Test and CI (Did Not Seek Instruction)

```
Sample    N  Mean  StDev  SE Mean
1       191  82.8   11.6     0.84
2       144  85.9   11.6     0.97


Difference = mu (1) - mu (2)
Estimate for difference:  -3.10
95% CI for difference:  (-5.62, -0.58)
T-Test of difference = 0 (vs not =): T-Value = -2.42  P-Value = 0.016  DF = 333
Both use Pooled StDev = 11.6000
```

Two-Sample T-Test and CI (Did Seek Instruction)

```
Sample   N  Mean  StDev  SE Mean
1       81  75.8   17.5      1.9
2       80  81.7   11.1      1.2


Difference = mu (1) - mu (2)
Estimate for difference:  -5.90
95% CI for difference:  (-10.47, -1.33)
T-Test of difference = 0 (vs not =): T-Value = -2.55  P-Value = 0.012  DF = 159
Both use Pooled StDev = 14.6733
```

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SOFTWARE

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