Evaluating an active learning approach to teaching introductory statistics: A classroom workbook approach

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Abstract

The study evaluates a semester-long workbook curriculum approach to teaching a college level introductory statistics course. The workbook curriculum required students to read content before and during class and then work in groups to complete problems and answer conceptual questions pertaining to the material they read. Instructors spent class time answering students' questions. The 59 students who experienced the workbook curriculum completed the Survey of Attitudes Toward Statistics (SATS) on the first and last day of the course. These students' post course ratings on the subscales of cognitive competence, affect and difficulty were all significantly higher than their pre course ratings. Additionally, the 59 students' post course ratings for these 3 subscales were also significantly higher than those provided by a comparison group of statistics students (sample size 235). The results indicated that the students experiencing the workbook curriculum (1) had more confidence in their ability to perform and understand statistics, (2) liked statistics more, and (3) thought statistics was *more* difficult than the comparison group. Additionally, these students' attitude scores were positively correlated with both GPA and performance on a comprehensive final exam. We discuss the various methodological problems faced by classroom researchers and suggest that, in some cases, assessing students' attitudes can be an effective solution to these methodological problems. We conclude that the workbook approach holds promise for teaching introductory statistics courses.

1. Introduction

1.1 Student attitudes and course evaluation

Measuring students' attitudes toward statistics both before and after completing a course is one way to assess a statistics curriculum's effectiveness (Harlow, Buckholder and Marrow, 2002; Manning, Zachar, Ray and Lo Bello, 2006; Sizemore and Lewandowski, 2009). Not only is attitude change an important outcome in its own right, but student attitudes toward statistics before and/or after taking a statistics course are also associated with other outcome variables. Specifically, more positive attitudes are associated with better performance in the course (Chiesi and Primi, 2009; Elmore, Lewis and Bay, 1993; Finney and Schraw, 2003; Roberts and Saxe, 1982; Schau, 2003, Schutz, Drogosz, White, and Distefano, 1998; Sorge and Schau, 2002) as well as increased future enrollment in additional statistics courses (Finney and Schraw, 2003).

The published classroom research that measures the *change* in students' attitudes toward statistics across a semester is mixed. Harlow et al. (2002) reported that their participants had significantly more positive attitudes about statistics after completing a statistics course. Specifically, their students had greater quantitative self-efficacy and significantly less quantitative anxiety. DeVaney (2010) found that students who took a graduate course online reported a decrease in statistics class anxiety and an increase in affect toward statistics but students who took the same course on campus did not report less anxiety or greater affect at the end of the course. It is noteworthy that the positive changes in attitude were small and only occurred in the online course in which initial anxiety was higher. Other researchers have also found mixed results. In their validation study, Cashin and Elmore (2005) used the Survey of Attitudes Toward Statistics Scale (SATS), the Attitude Toward Statistics Scale (ATS), and the Statistics Attitude Survey (SAS) to measure 342 students' attitudes toward statistics both before and after completing a statistics course. The SATS and the ATS each have subscales that measure different kinds of attitudes towards statistics (e.g., Affect, Cognitive Competence, Difficulty, Value, Effort, Course, and Field). Considering the subscales as distinct metrics the validation study actually measured seven different student attitudes both before and after a course. Only two of the seven attitudes were more positive after the course. Specifically, the students showed a positive attitude change on the ATS Course subscale which contained items like "I would like to continue my statistical training in an advanced course." Students also scored more positively on the SATS Affect scale which contained items like "I like statistics" and "I feel insecure when I have to do statistics problems," (reverse-keyed). The remaining five attitude measures showed no change. Further, the effect sizes for the two observed changes were both small.

It is clear that the statistics courses evaluated in the literature had different effects on students' attitudes toward statistics. Further, given the diversity of the results it is not possible to say what impact taking a statistics course has on students' attitudes. Knowing details about how these courses were taught (i.e., their respective course structures) might help explain these divergent results. [See Finney and Schraw (2003) for a detailed discussion of how using general versus task specific measures of self efficacy might also explain some of these divergent results].

1.2 Evaluating active learning approaches

Just as there are divergent results with respect to how a statistics course impacts students' attitudes toward statistics there are also divergent results with respect to the effectiveness of "active learning approaches" when teaching statistics. Some instructors/researchers have presented anecdotal evidence suggesting that active learning is effective (e.g., Knypstra, 2009; Bates Prins, 2009) and others have presented evidence that students' exam scores are higher when taught with an active learning approach than when taught with more traditional approaches (e.g., Christopher and Marek, 2009; Steinhorst and Keeler, 1995; Ryan, 2006; Yoder and Hochevar, 2005). Although numerous studies have found active learning to be effective, others have found it to have no effect (e.g., Pfaff and Weinberg, 2009) or even to hinder student performance (e.g., Weltman and Whiteside, 2010).

One of the reasons for the inconsistent results in the active learning literature is the enormous diversity of approaches that are referred to as "active learning." The only unifying characteristic seems to be that students are asked to "do something" (Page, 1990). We suspect that most advocates of active learning would not suggest that educators can have students "do anything" and expect positive results. Certainly, *what* students do and *how they think* about what they did determines whether a given active learning approach will be successful. For example, Pfaff and Weinberg (2009) held the view that actively generating data (and then analyzing that data) would increase students' understanding of the statistical concepts that underlie the statistical computations. They created clever hands-on data generation activities in which their students used cards to illustrate the central limit theorem as well as rolled dice and drew chips to compute confidence intervals. During each of these activities their students were asked some computational and/or conceptual questions but the primary focus was on *generating data* for the computations not on *explaining* underlying statistical concepts. After the hands-on data collection activities students' understanding of the underlying statistical concepts was assessed. Despite the fact that their students actively generated data, their students' post activity assessment performance was not better than their pre activity performance. We believe that Pfaff and Weinberg (2009) were correct to conclude that the physical act of generating data was not sufficient to produce learning. However, we do not think it is correct to conclude from their study that active learning approaches in general are ineffective.

In our view, active learning activities are effective to the degree that they encourage students to think about the underlying statistical concepts. If we are correct in this assertion, Pfaff and Weinberg's (2009) activities may have been ineffective because the data collection exercises were not used to *explain* underlying statistical concepts. Pfaff and Weinberg (2009) recognized this possibility in their discussion when they stated, ". . .when we use the modules in the future, we plan on giving students follow-up activities that have them spend more time describing key aspects of the concepts." If these same data collection activities included narratives that *explained* how the cards, dice, and chips illustrated key statistical concepts and students were required to answer questions about each concept as they performed each operation, it is possible that the activities would be more effective. We suspect that the key components of successful active learning approaches are using activities to explain concepts and requiring students to demonstrate that they understand these concepts by having them answer very specific rather than general questions.

Weltman and Whiteside (2010) were even more critical of active learning approaches than Pfaff and Weinberg (2009). They recently reported evidence that two active learning approaches were not only ineffective but also detrimental to some students. These divergent results might also be explained by analyzing the details of their study. Weltman and Whiteside (2010) compared three different ways of teaching binomial distributions, sampling distributions and calculating p-values in hypothesis testing. Seven sections of undergraduate business students were taught each of the above course topics with a traditional lecture, a hybrid presentation method, or an experiential learning method. The traditional method involved instructors presenting slides to students verbally. The hybrid method involved instructors presenting the same lecture slides in the same manner but with pauses after 15 minutes of lecture in which students were asked to answer questions pertaining to the previous 15 minute lecture. The active learning method involved students working in groups of two or three using "documentation . . . developed by the researcher." For example, pairs of students used "software that interactively display[ed] sampling distributions from different population distributions for selected sample sizes." After experiencing one of these teaching methods all students took a common 20 minute multiple choice quiz to measure what they learned.

Weltman and Whiteside (2010) reported an interaction between teaching method and student GPA. When the lecture method was used the performance of high, medium and low GPA students was significantly different as would be expected. However when the hybrid and "fully active" approaches were used, students with high, medium and low GPAs performed equally. In both conditions the performance of the high GPA students was significantly *less* than their performance under the lecture method.

The authors concluded, "that active learning is not universally effective and, in fact, it may inhibit learning for certain types of students." Further, they concluded, "It is possible that students with a high grade point average achieve a deeper level of learning when experiencing exposure to the maximum amount of instructor expertise and direction." Weltman and Whiteside's (2010) results clearly illustrate their high GPA students performed worse under their hybrid and "fully active" conditions. Obviously, these results challenge much of the anecdotal evidence used to support the effectiveness of "active learning" approaches to education. While the "active learning" methods evaluated by Weltman and Whiteside (2010) were not effective for all students, even detrimental to some, it is possible that other active learning methods are effective for all students.

Our study had three purposes: (1) to evaluate the effectiveness of a semester-long active learning statistics curriculum that differed significantly from the single day activities found ineffective by Weltman and Whiteside (2010), (2) to evaluate this active learning curriculum's impact on students' attitudes toward statistics, and (3) to determine if this active learning curriculum had a detrimental effect on the performance of high GPA students.

2. Research Design

2.1 Survey of Attitudes Toward Statistics (SATS-36)

We used the SATS-36 (Schau, Stevens, Dauphinee, and Del Vecchio, 1995) to measure students' attitudes toward statistics. Students completed the SATS on the first and last day of class. The SATS-36 is a 36 item scale with six subscales. Cronbach's alphas (α) were computed for each subscale using the pre test and post test data. Scales are generally considered reliable if α is at least .7 (Field, 2009). The six item affect subscale assessed students' feelings toward statistics (e.g., I will like statistics; I am scared by statistics) (pre test $\alpha = .88$, post test $\alpha = .87$). The six item cognitive competence subscale assessed students' beliefs about their ability to understand statistics (e.g., I can learn statistics; I will have trouble understanding statistics because of how I think) (pre test $\alpha = .93$, post test $\alpha = .86$.). The seven item difficulty subscale assessed students' beliefs about the difficulty of statistics (e.g., Statistics formulas are easy to understand; Statistics is a complicated subject) (pre test $\alpha = .91$, post test $\alpha = .81$). The four item interest subscale assessed students' interest in statistics (e.g., I am interested in being able to communicate statistical information to others; I am interested in using statistics) (pre test $\alpha = .89$, post test $\alpha = .84$). The four item effort subscale assessed students' beliefs about the amount of effort they would/did put in to the class (e.g., I plan to complete all of my statistics assignments; I plan to work hard in my statistics course) (pre test $\alpha = .83$, post test $\alpha = .71$). The nine item value subscale assessed students' beliefs about the usefulness of statistics in their lives (e.g., Statistics is worthless; Statistics should be a required part of my professional training) (pre test $\alpha = .85$, post test $\alpha = .58$). Although our reliability coefficient for the value subscale on the post test is low in our data, the scale has been shown to have adequate internal reliability in previous research (Cashin and Elmore, 2005; Hilton, Schau, and Olsen, 2004). All 36 SATS items use a 7-point likert scale (e.g., 1 = Strongly disagree to 7 = Strongly agree). Higher SATS scores indicate more positive attitudes toward statistics.

2.2 Students

Of the 86 students who enrolled in four sections of an introductory statistics course 59 completed both the pre SATS and post SATS. Sixteen students completed only the pre test, six completed only the post test, and five did not complete either test. Students who completed both surveys did not have significantly different GPAs than students who did not complete both surveys, $t(71) = .83$, $p = .40$, $\eta^2 = .01$, nor did they have significantly different scores on the final exam, $t(83) = .57$, $p = .57$, $\eta^2 = .004$. The 16 students who completed only the pre SATS were not significantly different from those 59 students who completed both on any pre SATS subscale nor did they differ on the final exam (all test statistics < 1 and p-values > .36).

Of the 59 students included in subsequent analyses, 15 were nursing majors, 11 were psychology majors, 11 were sociology/social work majors, 6 were pre med, 5 were biology majors, 3 were physical education, 2 were chemistry majors, 2 were Arts/Humanities majors, 1 was an education major and 3 students did not yet have a major. The mean age was 21.3 (SD = 5.4, median = 20, mode = 20). Thirteen students were male and 46 were female.

2.3 Class Structure

Four sections of approximately 22 students each were taught by two instructors. One instructor taught 3 sections of the course. The course covered the topics typically covered in a behavioral/social sciences statistics course. Specifically, the course included units on frequency distributions, central tendency, variability, z scores, z-tests, t-tests, oneway ANOVAs, factorial ANOVAs and correlations. All computations were performed using a calculator and/or a computer software package (i.e., PASW/SPSS).

Prior to class students read a short chapter (approximately five pages, single spaced) introducing the topic. These chapters were written specifically for this course and included a conceptual explanation of the topic, a completed computational example problem and an example of how to summarize the results of the analysis. After reading this information students were required to answer questions about the reading, to complete a computational problem, and to summarize the results of their computations. These questions were intended to be relatively simple and did not require application of the material. Answers to these problems were submitted prior to class via an online course management system. Students received feedback about their performance prior to class and were allowed to correct errors on homework questions. These homework assignments collectively accounted for approximately 17% of students' course grades.

The class period began with the instructor answering questions about the homework assignment, giving a brief lecture that reviewed the information in the reading, and introducing the activity for that day. The length of the lecture varied depending on student questions and the difficulty of the activity, but was typically 15-20 minutes. Class sessions were 75 minutes long occurring twice a week.

Each day's activity can best be described as a workbook. Each workbook presents a single statistical topic (e.g., variability, distribution of sample means, logic of hypothesis testing) that is divided into small subsections. As students worked through each subsection they answered increasingly complex conceptual and/or computational questions. For example, when completing the workbook on the distribution of sample means students worked with a population of four scores. First, students computed the mean and standard deviation of that population. Second, students followed instructions in the workbook and created the distribution of sample means for that population of scores. Third, students computed the mean and standard deviation of the distribution of sample means that they created. Fourth, they discovered that the mean of the distribution of sample means is equal to the mean of the original population. They also discovered the relationship between the standard deviation of the sampling distribution (i.e., $\sigma / \sqrt{n}$) and the standard deviation of the original population (i.e., σ). The activity ends with students discovering the Central Limit Theorem and recognizing that it is true for all populations. The entire distribution of sample means activity is provided in Appendix A. Answers to all activity questions were available to students so that they could check their answers while they worked. The instructor was also available to answer questions. Students were encouraged to complete workbooks with at least one other person, but group work was not required. At the end of the class period the instructor typically gave a brief lecture summarizing the main points of the activity and introducing the reading for the next day. The workbook answers were *not* graded. Grades in the course were based on aforementioned homework assignments, four exams, and a

cumulative final exam. All exam questions were novel, meaning no items had occurred previously in any homework or exam.

2.4 Comparison Group and Procedure

Because random assignment of individual students to sections was not possible we could not be confident that our four sections of the course would be equivalent in initial ability, motivation, or any other subject variables. In fact, during past semesters median exam scores across sections taught by the same instructor have differed by as much as 15%. Given that we could not be confident that our sections would produce an equivalent control group we chose to use a larger comparison group consisting of statistics courses with characteristics similar to ours. Specifically, we were able to obtain comparison data from 20 sections of statistics courses with data from 235 students. Similar to our courses, all comparison statistics sections satisfied a general education quantitative analysis requirement and the only pre-requisite for the course was algebra. Additionally, all sections had 30 or fewer students enrolled at the beginning of the semester. The comparison data was obtained from the lead developer of the SATS-36 (C. Schau, personal communication, June, 27, 2010). All four sections of our course were taught using the same workbook approach. Students from our sections and the comparison group answered identical SATS questions both before and after their respective courses.

3. Results

3.1 Statistical assumptions

Distributions of scores were explored to determine if normality assumptions were met. Z-scores for skewness and kurtosis along with inspection of the distributions revealed significant deviation from normality for four of the six SATS subscales (i.e., cognitive competence, value, interest, and effort). These subscales were analyzed using non-parametric statistics. The remaining two subscales (i.e., affect and difficulty) were analyzed using both parametric and non-parametric statistics and the patterns of results did not change. To simplify presentation of results, non-parametric statistics are reported below. A significance value of .01 (two-tailed) was used for all statistical tests.

3.2 Changes in student attitude toward statistics

We used Wilcoxon signed ranks tests to determine if students' scores on each of the SATS subscales changed during the semester. The results are shown in Table 1. Four of the six subscales produced significant effects. Students had significantly higher cognitive competence and affect toward statistics on the last day of the course than they did on the first day of the course. Additionally, students' predictions about the amount of effort they were going to put into the course on the first day were significantly higher than their ratings of the amount of work they said they put into the course on the last day of class. Finally, students' predictions about how difficult the course was going to be on the first day were significantly lower than their ratings of course difficulty after they completed the course. Interestingly, even though students reported liking statistics more at the end of the course their ratings of statistics difficulty were higher at the end of the course. Effect sizes are shown in the final column of Table 1. Field (2009)

indicates that when r is used to the measure effect size of a Wilcoxon sign rank test or a Mann Whitney U test r values between .3 and .5 reflect a medium sized effect. Three of the four observed effects exceeded the .3 effect size criterion.

Table 1. Change in students' attitudes from first to last day of course.

SATS subscale	Pre Mean (SD)	Post Mean (SD)	Pre Median	Post Median	z-score Wilcoxon Signed ranks test (z)[1]	p value (2-tailed)	Effect size (r): $z/\sqrt{N}$
Affect	4.11 (1.34)	4.86 (1.34)	4.17	5.25	-3.41	.001	.31
Cognitive competence	5.12 (1.29)	5.76 (1.13)	5.40	6.17	-3.34	.001	.31
Value	5.33 (0.90)	5.33 (0.84)	5.50	5.44	-.11	.911	.01
Difficulty	3.49 (1.03)	4.03 (1.00)	3.50	3.83	-3.17	.002	.29
Effort	6.45 (0.91)	6.00 (1.01)	6.75	6.25	-3.99	< .001	.37
Interest	4.85 (1.02)	4.61 (1.14)	5.00	5.00	-1.44	.149	-.13

*n = 59 for all tests

3.3 Comparison to SATS norms

To gauge the relative magnitude of the above changes in students' attitudes toward statistics we compared the changes we observed to those changes observed in a comparison group of statistics courses. The comparison data was obtained from the lead developer of the SATS-36 (C. Schau, personal communication, June, 27, 2010). All of the students in the comparison group took statistics at institutions similar to ours and in courses that were similar in size. Our institution is a four year university offering some masters degrees. Our statistics course can be taken to fulfill a general education quantitative analysis requirement and algebra is the only prerequisite. Our section enrollment is less than 30 students. We used SATS data from 20 introductory statistics sections with similar course characteristics. The number of students contributing to the comparison group for each subscale was 235. The six Mann Whitney U tests shown in Table 2 reveal that our sample was not significantly different from the comparison group on any pre course SATS subscale.

[1] All of the Wilcoxon's signed rank z scores are negative because the z for the Wilcoxon's signed rank test is computed based on the relative number of positive vs. negative post – pre change scores not directly from the pre or post values. A *negative* Wilcoxon's signed rank z score indicates that most of the post – pre differences were *positive*. Specifically the z is computed as follows: $z = T - (\text{mean } T) / \sqrt{(n(n+1)(2n+1))/24}$; where T = is either the sum of the ranked differences that were positive or the sum of the ranked differences that were negative, whichever one was smaller, mean $T = (n(n+1))/4$, and n = number of paired scores – the number of difference scores that were zero (Field, 2009).

Table 2. Comparison of pre course attitudes

SATS subscale	Sample Pretest Mean (SD)	Comparison group pretest Mean (SD)	Sample Pretest Median	Comparison group Pretest Median	Mann Whitney (z)	p value (2-tailed)	Effect size (r): z/√N
Affect	4.11 (1.34)	4.34 (1.14)	4.17	4.33	-1.14	.25	.07
Cognitive competence	5.12 (1.29)	5.04 (.96)	5.40	5.00	-1.11	.27	.06
Value	5.33 (0.90)	5.28 (0.92)	5.50	5.33	-.81	.42	.05
Difficulty	3.49 (1.03)	3.65 (0.71)	3.50	3.71	-0.98	.33	.06
Effort	6.45 (0.91)	6.43 (0.86)	6.75	6.75	-1.02	.31	.06
Interest	4.85 (1.02)	4.90 (1.22)	5.00	5.00	-.23	.82	.01

*N = 294; our n = 59; comparison n = 235.

However, the tests shown in Table 3 reveal that our sample was significantly different from the comparison group on 3 of the 6 post course SATS subscales (when using a significance level of .01, two-tailed). Specifically, our sections reported liking statistics significantly more than the comparison group did (i.e., more positive affect scores). Our students also reported significantly higher statistical cognitive competence (i.e., confidence in their ability to understand and perform statistical procedures) than the comparison group. While students in our sections thought statistics was harder than the comparison group they also liked statistics more than the comparison group.

Table 3. Comparison of post course attitudes

SATS subscale	Sample Posttest Mean (SD)	Comparison group Posttest Mean (SD)	Sample Posttest Median	Comparison group Posttest Median	Mann Whitney (z)	p value (2-tailed)	Effect size (r): z/√N
Affect	4.86 (1.34)	4.16 (1.41)	5.25	4.17	-3.60	<.001	.21
Cognitive Competence	5.76 (1.13)	4.93 (1.15)	6.17	5.00	-5.04	<.001	.29
Value	5.33 (0.84)	4.94 (1.20)	5.44	4.89	-2.18	.03	.13
Difficulty	4.03 (1.00)	3.63 (0.86)	3.83	3.57	-3.01	.003	.18
Effort	6.00 (1.01)	6.08 (0.96)	6.25	6.25	-.40	.62	.02
Interest	4.61 (1.14)	4.36 (1.52)	5.00	4.50	-1.01	.28	.06

*N = 294; our n = 59; comparison n = 235.

The results in Table 4 revealed that our sample experienced significantly larger change scores (i.e., post – pre) than the comparison group on three of the six SATS subscales (when using a significance level of .01, two-tailed). Our sample experienced a greater increase in how much they liked statistics (i.e., affect) and their confidence in their ability to perform statistics (i.e., cognitive competence). Interestingly, while our sample had more improved affect and cognitive competence ratings, they also produced a greater *increase* in statistics difficulty ratings.

Table 4. Comparison of change scores

SATS subscale	Sample Mean Difference (SD)	Comparison group Mean Difference (SD)	Sample Median Difference	Comparison group Median Difference	Mann Whitney (z)	p value (2-tailed)	Effect size (r): z/√N
Affect	.75 (1.49)	-.18 (1.33)	.70	-.16	-3.96	<.001	.23
Cognitive Competence	.64 (1.39)	-.12 (1.06)	.50	.00	-3.79	<.001	.22
Value	.00 (0.88)	-.34 (1.07)	.08	-.22	-1.87	.06	.11
Difficulty	.53 (1.11)	-.03 (0.79)	.33	.00	-3.52	<.001	.21
Effort	-.45 (1.13)	-.35 (1.14)	-.25	-.25	-.98	.33	.06
Interest	-.23 (1.27)	-.54 (1.27)	-.25	-.50	-1.54	.12	.09

*N = 294; our n = 59; comparison n = 235.

3.4 Students' cognitive competence and performance

The students in our statistics sections reported significantly higher confidence in their ability to perform statistics after completing the course and this increase in confidence was significantly greater than those produced in the comparison group. An important question is whether our students' higher confidence with statistics is associated with better performance. We correlated students' pre and post cognitive competence scores with their performance on the comprehensive final exam to address this question. The Spearman correlation between students' pre cognitive competence scores (i.e., students' reported confidence with statistics on the first day of class) and their score on the final exam explained 15% of the variance in exam performance, r_S (57) = .39, p = .002. Post cognitive competence (i.e., students' reported confidence approximately 3 to 5 days before the final exam) explained 30% of the variance in final exam performance, r_S (57) = .55, p < .001. Clearly, our students' self assessment of their statistics knowledge is positively associated with their actual performance.

3.5 GPA, Student attitudes and Performance

Weltman and Whiteside (2010) found that using an activity instructional method helped the performance of lower GPA students (GPA of 1.75 or lower) but hindered the performance of higher GPA students (GPA of 3.75 or higher). Although Weltman and Whiteside (2010) did not measure students' attitudes, given that students' level of achievement in statistics courses is frequently positively correlated with students' post course attitudes toward statistics (Chiesi and Primi, 2009; Elmore, et al., 1993; Finney and Schraw, 2003; Roberts and Saxe, 1982; Schau, 2003; Schutz, Drogosz, White, and Distefano, 1998; Sorge and Schau, 2002) it would not be surprising if a variable impacting students' performance in a course also impacted student's attitudes in a similar manner. Therefore, if our active learning approaches help the performance of lower GPA students and hinder the performance of higher GPA students one would expect a zero or negative correlation between GPA and post course attitudes (i.e., post SATS scores). However, we found 3 *positive* Spearman correlations. Specifically, after experiencing a semester of activity based instruction, higher GPA students liked statistics more, r_S (57) = .32, p = .02,

thought statistics were more difficult, r_S (57) = .44, p = .001, and were more confident in their ability to understand and perform statistics, r_S (57) = .39, p = .003, than lower GPA students. It is worth noting that the Spearman correlations between affect, difficulty, and cognitive competence and GPA before the course were not significant; they produced r_S of -.06, .17, and .13, respectively. In contrast to what would be expected given Weltman and Whiteside's (2010) conclusions, after experiencing an active learning workbook approach higher GPA students had *more positive* attitudes toward statistics than lower GPA students.

Finally, as a more direct test of the impact of the active learning workbook approach on the performance of students with differing GPA's we correlated our students' GPAs with their final exam performance. As would be expected, higher GPA students tended to perform better on the final exam, r (57) = .58, p < .001. Weltman and Whiteside (2010) found that after experiencing an active learning approach the performance of their high GPA students was suppressed to the achievement level of their medium GPA students. Contrary to their results, our higher GPA students performed better than our lower GPA students. It is also worth noting that the correlation between post course cognitive competence scores and final exam performance, r_S (57) = .55, p < .001, was approximately as large as the correlation between GPA and final exam performance, r_S (57) = .58, p < .001.

4. Discussion

4.1 Conclusions regarding the Workbook Approach and Active Learning

The activity based curriculum evaluated here produced significant positive changes in students' attitudes toward statistics. Specifically, after experiencing the workbook curriculum students liked statistics more and were more confident in their ability to perform and understand statistics. Interestingly, these same students gave higher difficulty ratings for statistics after taking the course than before. While some readers may assume that it is commonplace for statistics students to feel more confident about their statistical abilities after taking a course, the SATS data from 20 statistics sections with similar characteristics to ours suggest otherwise. In fact, none of the median SATS change scores (i.e., post – pre) for the comparison group were positive. When we compared our students' change in attitudes to the change in attitudes of students in the comparison group our students reported significantly larger positive changes in affect, cognitive competence, and statistics difficulty ratings.

We suspect that most statistics instructors would want their students to report that they like and understand statistics; however, we also suspect that most instructors are more concerned with their students' actual ability to perform and understand statistics. Therefore, it is important to illustrate that the students' more positive attitudes are associated with high performance. In our course the SATS cognitive competence scale was positively associated with performance on our comprehensive final exam. The strength of the association was approximately as strong as that between GPA and final exam performance.

We also found that the active learning approach used in our sections did not produce the detrimental learning effects for higher GPA students found by Weltman and Whiteside (2010). The differences in our findings may be attributed to procedural differences between our study

and the Weltman and Whiteside (2010) study. One of the most obvious differences between the designs was that our students engaged in active learning exercises (i.e., workbooks) every day in a semester long course whereas their students engaged in an active learning exercise once and a hybrid exercise once during the semester. If Weltman and Whiteside's students are similar to our students, their students would be more accustomed to being taught by lecture and therefore it seems reasonable that they might need some initial exposure to active learning exercises before the two methods could be fairly compared. Initially, some of our students resisted our workbook approach stating that they did not like having to "teach themselves." However, as our students became more accustomed to the workbook approach their resistance to the teaching method subsided. If Weltman and Whiteside's students were similar to ours, it is perhaps not surprising that they did not perform well after very limited experience with active learning exercises.

Another possible explanation for the differing results could be the activities themselves. The specific active learning approach evaluated here, a workbook approach, exposed students to course content by having them work through workbooks. Before class students were required to read short chapters, answer reading questions and to complete a short, "easy" homework. Requiring students to prepare before class was an important component of our workbook approach. During class, students were required to read the workbooks and then to demonstrate their understanding by working problems and/or by answering conceptual questions. Because students worked in the classroom, the instructor was able to provide quick assistance when it was needed. This educational approach enabled students to work on harder material when an expert was nearby and easier material outside of class. It also enabled students to work at their own pace. Additionally, instructors spent less time answering definitional or formulaic questions because students could look this information up in the workbook. Consequently, instructors spent more time answering conceptual questions and/or relating the material to "real world" situations that might be of interest to college students (e.g., evaluating the dangers of cell phone use while driving).

Anecdotally, one of the benefits of the workbook approach for our teaching was that it enabled us to interact with individual students more frequently than was possible when we taught via lecturing. It seemed to us that we more frequently called individual students by their names, we more frequently answered questions, and we more frequently encouraged individual's effort and progress. Recent educational research on "instructor immediacy" suggests that these kinds of instructor behaviors can increase student affect toward *instructors* as well as the *specific course* (Creasey, Jarvis, and Gadke, 2009; Mottet, Parker-Raley, Beebe, and Cunningham, 2007). Therefore, it is possible that some of our students' increase on the affect subscale of the SATS (i.e., how much our students like the *general topic of statistics*) was influenced by our "instructor immediacy behaviors" *if* you assume that a positive affect toward an instructor or a specific course can carry over to an overall area of study. However, we believe that it is a mistake to dismiss instructor immediacy effects as "procedural artifacts" or somehow less than real. Creasey, et al. (2009) point out that simply "smiling at students or responding effectively to their comments" is probably not sufficiently potent to turn them "into confident, self-directed learners" (p. 354). Instructor immediacy behaviors almost certainly interact with how the course material is organized and presented to produce outcomes. Likewise, in our view, our instructor immediacy behaviors are not likely to be sufficiently potent in and of themselves to make students like the general topic of statistics. We suspect that instructor immediacy behaviors

encourage students to engage with the instructor *and* the course material both of which frequently have positive academic outcomes. In fact, Creasey, et al. (2009) found that instructor immediacy behaviors were positively correlated with students endorsing more successful academic achievement orientations (i.e., instructor immediacy behaviors were associated with students trying harder). It is possible that our instructor immediacy behaviors interacted with the workbook packets to produce a change in student's attitudes toward statistics. It is important to recognize that if students develop more positive attitudes toward statistics (i.e., better achievement orientations) they may also develop better academic behaviors that in turn lead to better outcomes. In future research it may be possible to test the notion that the workbook approach helps change students' achievement orientations. Tentative support for the notion that the workbook approach changed more than *just attitudes* is found in the fact that students' own ratings of their ability to perform statistics were more correlated with final exam performance *after* completing the course. Given that students' statistics confidence ratings were more correlated with performance after the course, it is *possible* that as their attitudes improved across the semester their academic behavior improved as well which in turn lead to better performance on the final exam. Clearly, this is an important area for future research.

A common criticism of active learning approaches is that they sacrifice content coverage for direct experience. The workbook approach evaluated here did not. Instead it changed the mode in which students acquired information. In the typical lecture course students gain most of the course content from the instructor and text (if they read the text). In the present curriculum students read content in class and answered questions as they read. While the instructor did present information in mini-lectures students spent the majority of class time completing workbooks.

While encouraged by the fact that our workbook curriculum produced positive changes in students' attitudes that were significantly greater than is typical and that these attitude changes were associated with greater academic performance the workbook curriculum does require considerable flexibility on the part of instructors. Instructors must be comfortable (a) spending most of class time answering questions (b) having students working at diverse speeds, (c) answering similar questions for multiple student groups at different times, (d) rewording questions when students use inappropriate terms, and (e) applying statistical concepts to novel situations that students ask about. In sum, instructors adopting a workbook curriculum similar to ours need to be willing to give up some measure of control. While the method effectively controls the content that is being presented in the workbooks the students' questions are at times idiographic. Instructors must be comfortable "thinking on their feet". For our part, we found the unpredictability of students' questions to be invigorating. We had become bored with teaching statistics but when we changed to the workbook approach we were again excited about teaching the course.

4.2 Methodological Issues

The current evaluation study has methodological limitations. It was not possible to randomly assign individual students to sections and therefore a comparison group was used rather than a control group. While the comparison group was sufficiently large and it consisted of students taking statistics courses at institutions similar to our own, we do not know how the comparison

courses were structured and therefore we do not know to what degree these courses used active learning or lecture approaches. It is possible that the effects in this study resulted from an instructor effect (i.e., that both of us are such stellar instructors that any method we try would lead to these results). While a possibility, we hasten to mention that we have tried many things in our statistics classes that have not worked as well as the workbook approach evaluated here. Additionally, the present evaluation is limited because it focused on students' attitudes toward statistics rather than directly comparing students' actual performance. In classroom settings it is difficult to directly compare students' performance across courses because exams are frequently very different. In the present study, we did not have access to the exams used in any of the 20 comparison sections. Therefore, a more direct comparison of our students' statistical performance relative to that of other students was not possible.

While assessing students' actual performance seems the most obvious way to assess a curriculum's success, the reality is that comparing student performance across different curriculums creates many methodological problems. For example, it is easiest to compare students' performance when alternative curricula (i.e., teaching methods) cover identical content. However, to reliably measure what students have learned in a curriculum, instructors create items that are specific to that curriculum. To the extent that two curricula differ the tests used to assess each curriculum's impact *should* differ. When instructors/researchers emphasize easy curricula comparison by using a common test they often sacrifice some assessment accuracy. Ironically, if the teaching methods being evaluated are quite different a common test may not be a "fair" comparison. This was the case in this study. Our previous lecture course emphasized computation more and conceptual understanding less than our workbook approach. This difference in emphasis made comparing these two curricula via identical exams methodologically problematic.

Another challenging aspect of evaluating curricula arises from instructor and student differences across course sections. Even if the same instructor taught two sections of a course during the same semester using an "old" curriculum in one section and a "new" curriculum in the other wide differences in students' GPAs across course sections could still make direct comparisons of students' performance across sections problematic. Even if instructors could statistically correct for GPA it is possible that instructors expected their innovation to be beneficial and it was their expectation that boosted students' performance rather than the innovation. Alternatively, if an experimental section did not perform better, it is possible that the instructors were less familiar with the new curriculum which suppressed students' performance. It is important to recognize that even when researchers hold instructor and tests constant comparing students' performance across sections is problematic.

We are not trying to induce hopelessness in classroom researchers; rather our point is that direct measures of students' performance are not without their methodological limitations. While researchers should do their best to obtain direct measures of students' performance when evaluating their curricular changes, using standardized measures of students' attitudes can provide researchers with a common metric with which to compare curricula. Given that direct measures of performance are often difficult to interpret methodologically we argue that assessing students' attitudes can be valuable to classroom researchers. This argument is bolstered by the fact that student attitude measures are often correlated with performance (Chiesi and Primi,

2009; Elmore, et al., 1993; Finney and Schraw, 2003; Roberts and Saxe, 1982; Schau, 2003; Schutz, Drogosz, White, and Distefano, 1998; Sorge and Schau, 2002) and future enrollment choices (Finney and Schraw, 2003).

In sum, there are times when instructors cannot compare students' actual performance and/or times when doing so is less than optimal. In these situations comparing students' attitudes about course material may provide a solution to the curriculum evaluation problem, namely, a useful metric for assessing an individual curriculum's impact as well as a common measure for comparing the relative impacts of different curricula. In these situations student attitudes can be used instead of, or in addition to, measures of students' actual performance.

4.3 General Conclusion

In conclusion, the present study found that students who experienced the workbook approach had positive changes in their attitudes toward statistics. Further these positive changes were positively correlated with both students' final exam performance and their GPA. Collectively, these results suggest that the workbook approach shows promise as an educational approach in college statistics courses.

Appendix A

CHAPTER 7-1: DISTRIBUTION OF SAMPLE MEANS

LEARNING OBJECTIVES

After reading the chapter, completing the homework and this activity you should be able to do the following:

- Explain what a distribution of sample means is.
- Explain how a distribution of raw scores is different from a distribution of sample means that is created from those raw scores.
- Find the mean and the standard deviation of a distribution of sample means.
- Explain what the standard error of the mean measures.
- Compute sampling error.
- Describe how the standard error of the mean can be decreased.
- Explain why you would want the standard error of the mean to be minimized.

THE DISTRIBUTION OF SAMPLE MEANS AND SAMPLING ERROR

1. Why are researchers frequently forced to work with samples when they are really interested in populations?

2. When researchers work with samples, there is always the risk of large amounts of sampling error (i.e., getting a sample the does not represent the population accurately). Why is sampling error a problem for researchers?

If a study has too much sampling error it is not useful to researchers. In your last activity you learned that increasing sample size decreases sampling error. In this activity you will learn *why* increasing sample size decreases sampling error. You must understand the distribution of sample means if you hope to understand more advanced topics presented later in this course.
A distribution of sample means is defined as *all possible random sample means of a given size (n) from a particular population*.

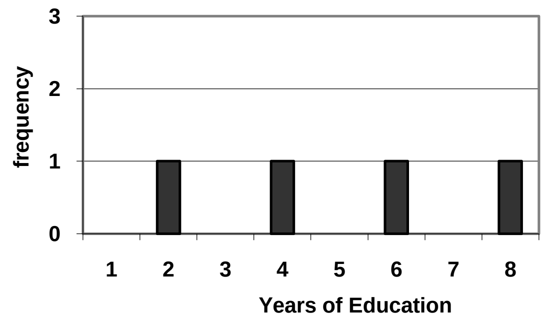
In this activity you are going to "build" a distribution of sample means and then use it to calculate the average amount of sampling error researchers should expect to have in their study. Working with a very small population is probably the easiest way to start. Thus, you are going to work with a population of just four people. Researchers are usually interested in much larger populations, but it is much easier to illustrate what a distribution of sample means is by working with a very small population.
Suppose there is a very small population of 4 billionaires who live in Norway. Further suppose that the data below represents the number of years of college/grad school each billionaire completed:

2, 4, 6, 8 (*note--this data is completely made up)

3. What is the mean for this population? **μ =** ________

4. What is the standard deviation for this population? **σ =** _________

Because there is just one of each score, the frequency distribution bar graph would be quite simple:



To create a distribution of sample means we need to obtain ALL possible RANDOM samples of a given size from this population. For this example, we are going to use a sample size of n = 2. Because the samples must be random we must be sure to sample with replacement. Thus, you would choose one score at random, put it back in the population, and then choose again at random. All possible random samples with n = 2 are listed below. The 16 samples below are ALL of the possible combinations of two scores from the population of 4 billionaires in Norway. Some of these samples represent the population much better than other samples. Which sample means represent the population well and which sample means do not? To answer this question compute the mean years of education for each of the 16 samples. Then determine which samples represent the population well and which do not.

5. Complete the table by finding the mean for each sample.

Sample	First Score	Second Score	Mean
1	2	2	
2	2	4	
3	2	6	
4	2	8	
5	4	2	
6	4	4	
7	4	6	
8	4	8	
9	6	2	
10	6	4	
11	6	6	
12	6	8	
13	8	2	
14	8	4	
15	8	6	
16	8	8	

6. The means you computed are ALL of the means that are possible when researchers take a sample of 2 scores from the population of 4 people. Collectively, the means are a *distribution of sample means*. Draw a frequency distribution graph of ALL THE POSSIBLE SAMPLE MEANS below:

7. You should know that some samples represent the population better than other samples and therefore have less *sampling error* than others. Each of the above sample means that are not exactly equal to the population mean of 5 (the population mean) have *sampling error*. Which samples have the most sampling error?

8. You should also know that ALL of the above sample means are possible when the researcher randomly selects a sample from the population. Looking at the distribution of sample means imagine that you randomly pick one sample mean from all possible sample means. Which sample mean are you most likely to pick and why?

9. How does the graph of the distribution of sample means (the frequency distribution you created in 6 above) *differ* from the graph of the original data (the frequency distribution under 4 above?) Are there any *similarities*?

10. Compute the mean and the standard deviation of the distribution of sample means. You should be able to use the Statistics mode on your calculator to obtain these numbers.

    a. Mean of ALL POSSIBLE sample means = ____________________________

    b. Standard Deviation of ALL POSSIBLE sample means =______________________

    CAUTION-when computing the standard deviation of all sample means n is the number of sample means NOT 2.

11. How does the mean of the distribution of sample means compare to the mean of the population?

12. The standard deviation of the distribution of sample means is ___________ than the *population* standard deviation because ____________.
    a) larger; sample means are *less* variable than individual scores in the population.
    b) smaller; sample means are *less* variable than individual scores in the population.
    c) larger; sample means are *more* variable than individual scores in the population.

d) smaller; sample means are *more* variable than individual scores in the population.

13. The exact relationship between the *population* standard deviation (σ) and the standard deviation of the distribution of sample means (abbreviated σ_M, called the standard error of the mean) is:

$$\sigma_M = \frac{\sigma}{\sqrt{n}}$$

*Note: n is the size of each sample (n = 2), not the number of possible samples that could be taken from the population.

Verify that this relationship was true by computing the standard deviation of the distribution of samples means (i.e., the standard error of the mean) from the population standard deviation and n. Compare this answer to the value you computed for the standard deviation of ALL sample means in 10b above.

14. The *population* standard deviation of 2.24 tells us that, on average, the individual scores were 2.24 away from the population mean of 5. What does the standard deviation of the distribution of sample means tell us? Explain how it is related to sampling error.

15. How could we make the standard error smaller?

16. Why would we want to make the standard error smaller?

THE CENTRAL LIMIT THEOREM

17. We are usually interested in larger populations and use larger samples than those used in this example. A population of 4 people and a sample size of 2 generated 16 possible random samples (and 16 possible sample means). Imagine how many different samples would be possible if you were interested in a large population (N = 100,000) and you used a large sample (n = 100). It would be *extremely* impractical to actually build the distribution of sample means every time you conducted a study. Fortunately, the same general principles (and the formula!) apply to larger data sets. Based on what you did above, describe the characteristics of all distributions of sample means. Collectively, these principles are called the **Central Limit Theorem**. This is a really important concept. It's worth understanding.

    a. The ***shape*** of the distribution of sample means will be:

    b. The ***mean*** of the distribution of sample means will be:

c. The ***standard deviation*** of the distribution of sample means will be:

18. Explain how you can use the **Central Limit Theorem** to compute the expected amount of sampling error in a given study *before* the study is conducted.

Note: The basis of this activity (i.e., generating an entire distribution of sample means from a population of four numbers) was adapted from Gravetter and Wallnau (2007).

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