Student Performance on Courseware Assignments in Statistics: A Comparative Analysis of Long-Term Student Progress and Contributions of Self-Efficacy, Gender, and Assignment Style

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College courses are often supplemented to some degree with an e-learning component. One common mechanism for e-learning is courseware, or instructional software designed to foster student learning (Rowley, 2005). Courseware is especially prevalent for courses in mathematics (Zucker, 2006).

The present study investigated student performance in undergraduate statistics courses where courseware use was required. A reasonable question to pose is whether a student's performance when using courseware is comparable to his/her performance on a similar "manual" assignment– one that is not computer-based, but covers generally the same content. If there is a difference between a student's performance on courseware and manual assignments, another worthwhile question to address is whether this difference persists or changes throughout the course, as students may become more comfortable with the courseware environment. The present study sought to address both of these questions.

Further, many factors may mediate student performance with courseware, and consequently, the student's success in classes that use courseware. Four student characteristics were examined as possible mediating factors in the student's performance on courseware assignments and subsequent performance in the course. Also examined were some details about the style of the courseware assignments.

Student Characteristics

Self-Efficacy

Three of the student characteristics examined in this study were forms of self-efficacy, or perceptions that students hold about their own abilities (Bandura, 1997). Students with higher levels of self-efficacy exert more effort on tasks, are more persistent in their work, and are more resilient to obstacles they encounter while working (Pajares & Schunk, 2001).

Self-efficacy was examined in three distinct areas because self-efficacy is task-specific (Pajares & Barich, 2005). The first area was computer self-efficacy, or students' belief in their computer abilities. Researchers have linked computer self-efficacy with students' willingness to use computers (Mcilroy, Sadler, & Boojawon, 2007), and with lower anxiety completing computer-based tasks (Wilfong, 2006).

The second area of self-efficacy was self-efficacy for self-regulated learning, or students' belief in their ability to use effective learning strategies (Pajares, 2002). Self-regulated learning has been identified as an important component for success in mathematics e-learning environments (Kramarski & Gutman, 2006). Researchers have also found associations between self-efficacy for self-regulated learning and students' degree of engagement with mathematics courseware (Spence & Usher, 2007).

The third area of self-efficacy was mathematics self-efficacy, or students' belief in their ability to succeed in a mathematics course. Mathematics self-efficacy has repeatedly been shown to predict students' mathematics achievement (Pajares & Schunk, 2001). Even in mathematics learning environments that incorporate courseware, mathematics self-efficacy has superseded computer self-efficacy and self-efficacy for self-regulated learning as the predominant predictor of mathematics achievement (Spence & Usher, 2007).

Gender

The other characteristic examined in the present study was student gender. A significant body of literature suggests that student gender may mediate performance in mathematics (Fan, Chen, & Mastumoto, 1997; Halpern, 1992; Hyde, Fennema, & Lamon, 1990). Gender differences have also been identified in student performance on computer-based learning tasks (Light, Littleton, Bale, Joiner, & Messer, 2000). Further, male students in high school and college report higher levels of mathematics self-efficacy than do their female counterparts (Pajares, 2005). Likewise, men often report higher levels of computer self-efficacy than do women (Whitley, 1997). Thus, student gender is an appropriate consideration when examining a mathematics course that incorporates courseware.

Methodology

Participants and Setting

Participants in the study were 115 students (43 males and 72 females) enrolled in an elementary statistics course for non-mathematics majors at a state-supported university in the southeastern United States. Each participant was enrolled in one of four sections of the same statistics course. Two of the sections were taught by one instructor, who will be designated as "instructor #1". The other two sections were taught by another instructor, who will be designated as "instructor #2." Some students withdrew from the course, and others who had agreed to participate were eliminated from the data set because they did not complete all of the assignments selected for the study. The remaining students comprise the 115 participants noted above. Of these, 60 were enrolled in one of instructor #1's sections (21 males and 39 females), and 55 were enrolled in one of instructor #2's sections (22 males and 33 females).

All sections of the statistics course used the same text, *The Basic Practice of Statistics* (Moore, 2006) and the same courseware, StatPortal, which is designed to accompany the text. The courseware included a complete electronic version of the text (an e-book), which students were encouraged to use. The courseware also provided a series of audiovisual tutorials for each chapter. The courseware allowed each instructor to create online assignments and assessments for students, and to structure the assignments in a variety of ways. Assignments could contain any number of questions of various formats, such as multiple choice, matching, multi-select (multiple choice with more than one correct answer), and fill-in-the-blank.

Instructors were also able to define a number of parameters governing the style of the assignment. Based on these parameters, instructors identified each assignment as either a homework assignment or a quiz. Both instructors defined homework assignments so that students could save work and resume later, students could see all assigned questions on one screen, and students could answer questions in any order. Both instructors also configured homework assignments so that students could work and submit the homework assignment more than once. After each submission, the student received a score and feedback on items missed, but was not explicitly given the correct answers. Also, although questions in the homework assignments were given in the same order and covering the same content using the same question scenarios in each attempt, actual numeric values given in the question could vary from one attempt to the next. Although both instructors assigned a deadline for completion of each assignment, the homework assignments were otherwise not timed; both instructors allowed students to spend as much time as they chose on the assignment, up to the submission deadline. After the submission deadline, a student received the highest score out of all the attempts (s)he had submitted for that homework assignment. However, instructor #1 allowed students to submit each StatPortal homework assignment up to 5 times. Instructor #2 allowed only 2 submissions of each StatPortal homework.

Both instructors defined StatPortal quizzes with parameters different from those of the homework. Neither instructor allowed students to save and resume work on quizzes. Both instructors allowed students to attempt the quiz twice. Instructor #1 assigned each student the highest quiz score from the two attempts. Instructor #2 assigned each student the average of the two scores if the quiz was attempted twice. Instructor #1 defined remaining parameters similarly to those of the StatPortal homework: All questions were shown on one screen, students could answer questions in any order, and no time limit was imposed. By contrast, instructor #2 defined the quizzes so that they were timed (15 – 20 minutes, depending on content). Students also could only see one question at a time and were not allowed to backtrack or skip forward; that is, students were required to answer the quiz questions in the order they were presented. Instructor #2 also scrambled the order of questions from one quiz attempt to the next.

Because the style of courseware assignments and assessments differed substantially between the two instructors, data collected were analyzed as two separate groups of data– one data set for instructor #1 (with n=60) and another data set for instructor #2 (with n=55).

Variables and Instruments

Each variable in the study is defined below. Terms defined by the author are placed in quotes. An abbreviation for each variable is given in brackets; abbreviations are used in the results section to allow more space for figures in the tables. For all three self-efficacy variables (listed at end), student answers were chosen from a 6-point Likert type scale. The student's score for each construct was the average of all items on the instrument; this average ranged from 1 to 6.

"*Courseware beginning*" [C-beg] – Courseware performance at the beginning of the course was measured by averaging the student's first StatPortal homework assignment and first StatPortal quiz.

"*Manual beginning*" [M-beg] – Performance on non-courseware (or manual) assignments at the beginning of the course was measured by averaging the student's first written assignment and the student's first written assessment (which was an in-class test for both instructors).

"*Advantage beginning*" [Adv-beg] – The advantage of courseware assignments and assessments over manual assignments and assessments at the beginning of the course was measured by subtracting the manual beginning average from the courseware beginning average. A positive result indicates that the student performed better overall on the early courseware assignments and assessments than on the manual ones. A negative result indicates that the student performed worse overall on the early courseware assignments. The magnitude of the difference indicates the degree of better or worse performance.

"*Courseware end*" [C-end] – Courseware performance at the end of the course was measured by averaging the student's last StatPortal homework assignment and last StatPortal quiz.

"*Manual end*" [M-end] – Performance on manual assignments at the end of the course was measured by averaging the student's last written assignment and the student's last written assessment (an in-class test for both instructors), *excluding* the final exam.

"*Advantage end*" [Adv-end] – The advantage of courseware assignments and assessments over manual assignments and assessments at the end of the course was measured by subtracting the manual end average from the courseware end average. A positive result indicates that the student performed better overall on the last courseware assignments and assessments than on the last manual ones. A negative result indicates that the student performed worse overall on the last courseware assignments. The magnitude of the difference indicates the degree of better or worse performance.

"*Courseware gain*" [C-gain] reflects the degree to which a student's performance on courseware assignments changed from the beginning to the end of the course. A positive result indicates that the student's performance on courseware assignments improved from the beginning to the end of the course. A negative result indicates that the student's performance on courseware assignments declined.

"*Manual gain*" [M-gain] reflects the degree to which a student's performance on manual assignments changed from the beginning to the end of the course. A positive result indicates that the student's performance on manual assignments improved from the beginning to the end of the course. A negative result indicates that the student's performance on manual assignments declined.

"*Advantage gain*" [Adv-gain] reflects the direction and extent of any change in the advantage of a student's courseware performance over manual assignment performance. A positive result indicates that any discrepancy favoring manual assignments diminished, and/or any discrepancy favoring courseware assignments increased. A negative result indicates that any discrepancy favoring courseware assignments diminished, and/or any discrepancy favoring manual assignments increased.

Mathematics performance [Perf] represents students' performance in the statistics class overall, as reflected in their final course average, given as a percentage. Note that this variable (mathematics performance) together with all variables listed above are collectively referred to as the "performance variables" in the study throughout the remainder of this report.

Computer self-efficacy [CSE] represents students' confidence in their ability to use a computer effectively. The 10-item scale was a subscale adapted from a scale developed and validated by Murphy, Coover, and Owen (1989). A sample item is "I feel confident working on a computer." Researchers have obtained alpha coefficients of .90 to .96 using variations of this scale (e.g., Durndell & Haag, 2002; Torkzadeh, Pflughoeft, & Hall, 1999). Cronbach's alpha was .90 in the present study.

Gender represents the students' gender (female or male). Females were coded as zero (0) and males were coded as one (1).

Self-efficacy for self-regulated learning [SE-SR] represents students' confidence in their ability to use self-regulated learning strategies. The seven-item scale is a subscale adapted from Bandura's Multidimensional Self-Efficacy Scales (see Zimmerman, Bandura, & Martinez-Pons, 1992). The scale was specifically adapted to refer to self-regulated strategies for learning *statistics*; thus, the questions are worded to target statistics specifically. A sample item is “How well can you motivate yourself to do statistics assignments?” Researchers using variations of this scale have reported alpha coefficients from .80 to .87 (e.g., Zimmerman et al., 1992). An alpha of .85 was obtained in this study.

Mathematics self-efficacy [MSE] reflects students’ belief in their mathematical ability. Because student overall performance in the class was represented by their final course average, mathematics self-efficacy was defined as students’ confidence that they could make a certain grade in the course. Again, because this was a statistics course, items were worded to focus on performance in that statistics course. A sample item is “How confident are you that you will finish your statistics course this semester with a grade of B or better?” This scale was developed in consultation with Bandura’s (2006) *Guide for Constructing Self-Efficacy Scales*; similar scales are prevalent in the field. Researchers using similar academic self-efficacy scales have obtained alpha coefficients ranging from .86 to .93 (e.g., Pajares & Barich, 2005; Spence & Usher, 2007). Cronbach’s alpha of .93 was obtained in the present study.

Analyses

Because of the substantially different style of courseware assignments between the two instructors, all analyses were conducted separately for each of the two groups (students of instructor #1 and those of instructor #2.) Descriptive statistics and zero-order calculations were calculated for all variables in each analysis and t-tests were used to compare the mean scores of each variable between the two groups. Gender comparisons were performed using t-tests within each group to determine if men and women differed significantly on any of the research variables. In addition, dependent samples (paired) t-tests were used within each group to determine: 1) if differences between performance on manual and courseware assignments were significant, both at the beginning and at the end of the course; and 2) if differences in performance at the beginning and at the end of the course were significant.

A series of regression analyses were used to determine the extent to which each of the three self-efficacy variables predicted each of the performance variables. In cases where more than one self-efficacy variable significantly predicted a performance variable, multiple regression analysis was used to determine how the relevant self-efficacy variables jointly predicted the student’s performance. Multiple regression models were constructed with all possible combinations of relevant predictor variables (those that by themselves predicted the performance variable in question).

Results

Descriptive statistics for each of the two groups are given in Table 1, together with results of t-tests for mean differences between the groups.

Table 1. Means and Standard Deviations for All Variables by Instructor

	Instructor #1		Instructor #2			
Variable	M	SD	M	SD	t	Effect size
C-beg	85.983	14.357	84.945	11.265	0.433	0.078
M-beg	89.583	4.178	85.572	5.165	4.553***	0.800
Adv-beg	-3.600	13.456	-0.627	10.065	-1.349	0.238
C-end	87.667	14.119	91.927	12.881	-1.692	0.190
M-end	85.156	10.960	87.909	5.454	-1.727	0.310
Adv-end	2.511	16.611	4.019	11.654	-0.567	0.067
C-gain	1.683	18.263	6.981	12.714	-1.818	0.230
M-gain	-4.428	9.777	2.336	5.052	-4.716***	0.791
Adv-gain	6.111	19.781	4.645	12.553	0.478	0.064
Perf	85.567	8.412	83.510	7.714	1.368	0.240
CSE	4.900	0.718	4.787	0.757	0.820	0.150
SE-SR	4.198	0.927	4.278	0.935	0.462	0.087
MSE	4.530	1.172	4.341	1.054	0.905	0.169

***$p < .001$

The only areas in which the two groups differed significantly were with respect to the manual (i.e., *non*-courseware) assignments. On average, students of Instructor #1 performed significantly higher on the first manual assignment and assessment than did students of instructor #2. Then, students of instructor #1 declined in their performance of manual assignments and assessments on average, showing a negative "gain" (improvement). Yet students of instructor #2 raised their average performance on manual assignments and assessments. Thus the gain (improvement) on manual assignments was significantly higher for students of instructor #2.

The results of the paired t-tests for performance differences between courseware assignments and manual assignments are shown in Table 2 for each instructor's students. Both instructors had differences favoring manual assignments at the beginning of the course, but the difference was significant only for students of instructor #1. Likewise, both instructors had performance differences favoring courseware at the end of the course, but the difference was only significant for students of instructor #2.

Table 2. Comparison of Performance on Courseware and Manual Assignments for Each Instructor

Instr.	Assignment Performance Comparison	Mean Difference	t
#1	Courseware & manual at beginning of course (C-beg, M-beg)	-3.600	2.192*
#1	Courseware & manual at end of course (C-end, M-end)	2.511	0.305
#2	Courseware & manual at beginning of course (C-beg, M-beg)	-0.627	0.464
#2	Courseware & manual at end of course (C-end, M-end)	4.019	2.556*

*p < .05

The results of the paired t-tests for performance differences between beginning of course and end of course are shown in Table 3 for each instructor's students. Students of instructor #1 showed a significant decline in performance on manual assignments, but not on courseware assignments, which were higher on average at the end of the course than at the beginning, but not significantly so. Students of instructor #2 showed significant improvement on both types of assignments from the beginning of the course to the end. Students in both groups showed a significant increase in their performance on courseware assignments *relative to* that of their manual assignments; the performance difference favored manual assignments for both groups at the beginning of the course, but favored courseware assignments for both groups at the end of the course. The increase in the students' performance advantage on courseware assignments over manual assignments was significant for both groups.

Table 3. Comparison of Performance at Beginning and End of Course for Each Instructor

Instr.	Performance Comparison	Mean Difference	t
#1	Courseware at beginning and end of course (C-beg, C-end)	1.683	0.478
#1	Manual at beginning and end of course (M-beg, M-end)	-4.428	-3.508**
#1	Courseware ***advantage*** at beginning and end (Adv-beg, Adv-end)	6.111	2.393*
#2	Courseware at beginning and end of course (C-beg, C-end)	6.981	4.072***
#2	Manual at beginning and end of course (M-beg, M-end)	2.336	3.430**
#2	Courseware ***advantage*** at beginning and end (Adv-beg, Adv-end)	4.645	2.745*

*p < .05; **p < .01; ***p < .001

The results of selected t-tests for gender differences in each group are shown in Table 4. As very few significant differences emerged, only variables for which significant differences were detected are shown. Among students of instructor #1, females scored significantly higher on manual assignments at the beginning of the course. Among students of instructor #2, males reported significantly higher computer self-efficacy and had a significantly greater performance advantage on courseware assignments over manual assignments at the beginning of the course. This significant gender gap in performance advantage on courseware assignments did not persist at the end of the course.

Table 4. Significant Gender Differences Within Each Group

		Male		Female			
Instructor	Variable	M	SD	M	SD	t	Effect Size
#1	M-beg	87.968	4.387	90.453	3.842	-2.184*	0.590
#2	Adv-beg	2.545	8.703	-2.742	10.474	2.033*	0.526
#2	CSE	5.027	0.636	4.627	0.798	2.060*	0.526

*p < .05

Zero-order correlations among all research variables are shown in Table 5 for each instructor.

Table 5. Zero-Order Correlations for Variables in the Study by Instructor

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 C-beg	---	.35**	.96***	.18	.08	.10	-.65***	-.06	-.57***	.22	.12	.30*	.37**
2 M-beg	.45**	---	.07	.19	.46***	-.14	-.13	.09	-.16	.79***	.17	.43**	.62***
3 Adv-beg	.89**	-.01	---	.13	-.06	.15	-.65***	-.09	-.56***	-.01	.08	.19	.20
4 C-end	.45**	.35**	.33	---	.14	.76***	.63***	.08	.55***	.23	.21	.27*	.11
5 M-end	.29*	.55***	.04	.43**	---	-.54***	.05	.93***	-.42**	.80***	.01	.40**	.46**
6 Adv-end	.36**	.13	.34*	.91***	.00	---	.51**	-.55***	.74***	-.33**	.18	-.04	-.21
7 C-gain	-.43**	-.04	-.46***	.61***	.18	.60***	---	.11	.87***	.00	.07	-.03	-.20
8 M-gain	-.15	-.43**	.06	.10	.52***	-.13	.23	---	-.40**	.56***	-.06	.26*	.25
9 Adv-gain	-.38**	.13	-.49***	.58***	-.03	.66***	.92***	-.17	---	-.27*	.09	-.16	-.31*
10 Perf	.56***	.78***	.23	.55***	.76***	.25	.06	.02	.05	---	.06	.49***	.63***
11 CSE	.39**	.12	.38**	.11	.21	.02	-.24	.11	-.28*	.19	---	.08	.40**
12 SE-SR	.26	.13	.23	.24	.35**	.10	.01	.25	-.09	.35**	.38**	---	.42**
13 MSE	.27*	.39**	.11	.40**	.59***	.16	.16	.24	.06	.60***	.21	.53***	---

Note: Correlations above the diagonal are for students of instructor #1; correlations below the diagonal are for students of instructor #2.
*p < .05; **p < .01; ***p < .001

For instructor #1, student performance on courseware assignments at the beginning of the course correlated significantly with self-efficacy for self-regulated learning and with mathematics self-efficacy, but not with computer self-efficacy. By contrast, for instructor #2, student courseware performance at the beginning of the course was significantly associated with computer self-efficacy, as well as with mathematics self-efficacy. Similarly, among students of instructor #2, those with higher computer self-efficacy were more likely to demonstrate a performance advantage on courseware assignments over manual assignments. No such relationship emerged among students of instructor #1. Finally, the degree to which a student's courseware performance advantage increased from the beginning to the end of the course (Adv-gain) was significantly associated with computer self-efficacy for students of instructor #2, but not those of instructor #1. Also noteworthy is that students' performance advantage on courseware assignments was not associated with any of the self-efficacy variables at the end of the course, even though such an association existed at the beginning of the course for students of instructor #2.

Further, for instructor #1, student performance on courseware assignments at the end of the course was significantly associated with self-efficacy for self-regulated learning, but not with any other type of self-efficacy. For students of instructor #2, performance on end-of-semester courseware assignments was associated with mathematics self-efficacy and was not associated with any other prediction variable in the study. Finally, overall performance in the course for both groups was significantly associated with both self-efficacy for self-regulated learning and with mathematics self-efficacy.

Other significant correlations are evident in the table, and many of these are easily explained by the relationships that must clearly exist among the variables. For instance, performance on courseware assignments at the beginning of the course (C-beg) is negatively associated with a *gain* in courseware assignment performance (C-gain), because students who were already performing well on courseware assignments did not have much room to improve. Although many similar patterns are evident in the data and correlations, these patterns and their likely explanations are left for the reader to discern.

Some student outcomes were significantly associated with more than one type of self-efficacy. For these variables, a multiple regression analysis was conducted to determine how the combined self-efficacy variables jointly predicted the outcome. In most cases, only one of the self-efficacy variables in question made an independent contribution to the regression model.

In particular, for instructor #1, self-efficacy for self-regulated learning was the only significant predictor of improvement on manual assignments (M-gain). Self-efficacy for self-regulated learning and mathematics self-efficacy each predicted performance on courseware assignments at the beginning of the course and on manual assignments at both the beginning and end of the course. However, in all three cases, multiple regression analyses revealed that only mathematics self-efficacy independently predicted performance when both variables were in the regression model. The only exception to this pattern was on overall course performance, where both types of self-efficacy made an independent contribution in jointly predicting achievement. The standardized beta coefficients for this multiple regression model predicting overall student achievement were 0.271 for SE-SR ($p < .05$) and 0.514 for MSE ($p < .001$). The model was significant ($p < .001$) and accounted for 44% of the variance in overall achievement.

Similarly, for instructor #2, mathematics self-efficacy was the only significant predictor of student performance on manual assignments at the beginning of the course and on courseware assignments at the end of the course. However, when used in separate bivariate regression analyses, mathematics self-efficacy and computer self-efficacy each predicted student courseware performance at the beginning of the course, the two variables were used together in a multiple regression model, which revealed that only computer self-efficacy made an independent contribution when both predictors were in the model. Likewise, mathematics self-efficacy and self-efficacy for self-regulated learning each predicted performance on manual assignments at the end of the course, as well as on overall performance in the course. Yet multiple regression models for each outcome again revealed that mathematics self-efficacy made the only independent contribution to the model when both variables were in the model together.

Discussion

Several previous findings are supported by the current study. These include the contribution that computer self-efficacy and self-efficacy for self-regulated learning can each make to a student's performance on a computer-based assignment. In addition, the present study upholds the consistent finding of many researchers that mathematics self-efficacy is a particularly reliable predictor of mathematics achievement, seemingly regardless of variations in the learning environment.

Also noteworthy is the finding that as the course progressed, students in both groups improved their performance on courseware assignments more than on their corresponding manual assignments. This pattern suggests that students learned to leverage advantages of working with courseware to their benefit.

Finally, the analyses seem to suggest that performance patterns and associations differed somewhat by instructor. Recall that instructor #1 arranged courseware homework assignments so that students could attempt each one up to 5 times, whereas instructor #2 only allowed students to attempt such assignments twice. It is possible that this and other variations in assignment style (as noted previously) are responsible for some of the differences that emerged in the analysis of the two groups. In particular, computer self-efficacy did not predict any performance variables for students of instructor #1. Possibly these students were able to get more comfortable with the courseware assignments by attempting them several times, so that whether they had computer self-efficacy or not, they were able to succeed on those assignments, even at the very beginning of the course.

Both of the above observations support the notion that, given time and opportunity, students will learn to work more effectively with courseware, thereby increasing its benefit. Instructors can also take steps to structure their assignments in such a way that students acclimate more easily to using courseware.

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