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The Impact of Adaptive Learning in Principles of Microeconomics

Doris S. Bennett
Jacksonville State University

Cynthia S. McCarty
Jacksonville State University

Michael S. Carter
Jacksonville State University

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Doris Bennett
Jacksonville State University, Jacksonville, AL, 36265
dbennett@jsu.edu

Cynthia McCarty
Jacksonville State University, Jacksonville, AL, 36265
cmcarty@jsu.edu

Shawn Carter
Jacksonville State University, Jacksonville, AL, 36265
scarter@jsu.edu

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Abstract:
The spread of Covid-19, which forced almost all learning to move to online in March, 2020, abruptly increased the number of undergraduates taking at least one online course by approximately 177% between the fall of 2019 and the spring of 2020 (Koksal, 2020; Carey, 2020; National Center for Education Statistics, 2020). Even without the Covid-19 disruption, online education has become increasing prevalent due to the decreasing allocation of resources to higher education and the pressure on college administrators to make a college education effective, affordable, and accessible for more students. Originally online instruction differed from in-class instruction only be the method of delivery of the material, viewing a lecture online versus being present in a live classroom lecture. Although there have been many studies on the effectiveness of traditional online instruction over the last several decades, there have been fewer studies on the efficacy of the relatively new adaptive learning courseware. This initial study found that adaptive learning had a consistently positive and statistically significant impact on all principle of microeconomics students in the study, regardless of aptitude, ethnicity, and gender. However, students with high aptitudes appeared to benefit more from adaptive learning than their peers.

Introduction

Over the last several decades, academic instruction has been steadily changing from traditional in-person lectures with printed textbooks to computer-based instruction. According to the National Center for Education Statistics, online learning increased steadily between the fall semesters of 2012 and 2019 from approximately 25.8% of undergraduate students to 36% of undergraduate students. This represented a change in total undergraduate students taking at least one course online from 4.6 million students in 2012 to 6.1 million students in 2019. The spread of Covid-19, which necessitated lockdowns and social distancing and forced almost all learning to move to online in March of 2020, abruptly increased the number of undergraduates taking at least one online course from 6.1 million students in the fall of 2019 to approximately 16.9 million in the spring of 2020 (Kosar, 2020; Carey, 2020; National Center for Education Statistics, 2020). Education may have changed permanently as a result of the Covid-19 disruption. It is likely that institutions will continue to increase online courses, especially considering the diminishing allocation of resources for higher education purposes (Luthra and Mackenzie, 2020; Yu and Wu, 2016; Mayer, 2019). With online education becoming even more prevalent in the future, it is essential for instructors to employ methods that increase its quality and effectiveness. The purpose of this study is to measure the effectiveness of adaptive learning in principles of microeconomics. This should be a contribution to economics education, as well as to the evaluation of the efficacy of adaptive learning, a relatively new technology, on online learning.

Elements of Adaptive Learning

Adaptive learning is an online instructional technique that assesses what a student already knows and introduces the student to new concepts when they have mastered the current material. It provides personalized learning to large groups of students, ensuring that they receive individual remediation on a topic where they are weak and then introduces new material at the appropriate point. An adaptive learning system learns from students' responses and adjusts the path and pace of learning to the individual student. Unlike most traditional online and lecture college courses, students receive immediate feedback as they answer questions with correct solutions and step-by-step instructions provided. Bashir, Kabir, and Rahman (2016) point out the importance of feedback in the learning process and note that many college classes continue to provide the traditional methods of feedback on a limited number of graded assignments. In place of a few high-stakes assessments, they recommend more low-stakes assessments, like the adaptive learning exercises where students get an immediate evaluation of their progress.

Adaptive learning courseware can present the material in a variety of formats, including text, videos, graphics, and simulations. It provides immediate feedback to aid the student in following their individual learning path. Using adaptive learning courseware in a learning management system enables the instructor to monitor progress for large groups of students. Because it moves away from "one size fits all" instruction and tailors learning to the individual student based on their interaction with the material, adaptive learning often produces a higher level of student engagement. Student engagement is further realized due to adaptive learning being compatible with almost any electronic device, allowing students anywhere to engage in learning (Yakin, 2021; O'Sullivan et al, 2020). Finally, adaptive learning discourages cheating because the content and tests are individualized based on a student's learning path and prior achievement; therefore, the content of each assignment will vary based on a student's individual needs (Phillips and Johnson, 2011; Educause Learning Initiative, 2017; Adaptive Learning Demystified, 2019).

Even before the pandemic forced most instruction to transfer online, many organizations have expressed interest in adaptive learning. A 2015 survey of 110 higher education professors and administrators revealed that the respondents viewed adaptive learning technology as the most important instructional development likely to improve the quality of student learning (Kurzweil, 2016). Additionally, in 2016 the Gates' Foundation partnered with the Association of Public and Land-grant Universities and gave grants to seven member universities for the implementation of adaptive learning software in large general education classes. Also, in 2017 the National Academy of Engineering identified personalized learning as one of the Grand Challenges for Engineering in the 21st century (Clark and Kaw, 2019). Furthermore, in 2017 the U.S. Department of Education recognized adaptive learning technology as the next generation in assessment. Adaptive learning was identified by the New Media Consortium and Educause as an important technology likely to impact higher education in the future (Educause Learning Initiative, 2017).

Literature Review

Although a study of principles of microeconomics students using LearnSmart adaptive courseware by McGraw-Hill, Gebhardt (2018) found that among 109 principles of microeconomics students, those who completed at least some of the adaptive learning assignments scored significantly better on easy and moderate exam questions than their peers, most research on the efficacy of adaptive learning has been focused on areas and disciplines other than college economics courses. Hubalovsky, Hubalovska, and Musilek (2019) found that adaptive learning increased the ability to remember, understand, and apply multiplication in a group of primary school children, ages six to ten. Phillips and Johnson (2011) compared accounting online homework systems which provide practice problems where students are given the correct answer with adaptive learning systems in accounting where students are provided with the correct answer and step-by-step tutoring on the process used to work the problem. They found that students' ability as measured by improvements on test scores as the semester progressed increased significantly more for the students using the adaptive learning system compared to those who used the online homework system. Johnson, Phillips, and Chase (2009) found that sophomore accounting students who used an adaptive learning system improved their test scores by 27% compared to an 8% improvement for students using the textbook as their sole reference for solving accounting problems. Sun, Norman, and Abdourazakou (2018) found that 310 management and marketing students were more satisfied with an interactive, adaptive learning textbook than with a traditional printed textbook or e-book. Clark and Kaw (2019) also reported increased satisfaction with an adaptive learning system compared to a traditional textbook among students in mathematics for engineering classes. Frankola (2001) found that corporate learners were more likely to finish online training courses when interactive systems were used. Griff and Matter (2013) found significant differences in pre-test and post-test scores for anatomy and physiology students at two of six large universities that used an adaptive learning system compared to students using a traditional textbook. Yakin and Linden (2021) report higher scores on exams and positive evaluations of adaptive learning among dental students who used adaptive learning courseware. When adaptive learning courseware was implemented in introductory biology courses at the University of Mississippi, Colorado State University, Portland State University, and the University of Central Florida between 2016-2019, students' grades improved and students' responses to the courseware were positive in most cases (O'Sullivan et al 2020). Linden, Pemberton, and Webster (2019) found that 96% of anatomy students felt that adaptive learning courseware increased their engagement in the course.

In a survey of 675 professors teaching principles of economics conducted in late 2019 into March 2020 when the pandemic forced instruction to move online, Asarta, Chambers, and Harter (2020) found that traditional "Chalk and Talk" lectures and printed textbooks were used very frequently as the method of instruction in principles of economics, while adaptive learning was almost never used. Many of the earlier studies comparing online vs traditional learning for economics students were conducted before adaptive learning became widely available. Furthermore, many of these studies reported characteristics of students who chose online courses instead of traditional lecture courses. (Brown and Liedholm, 2002; Shoemaker and Navarro,2000; Keri, 2003) Results were mixed in the studies that compared the performance of online students with those in traditional lecture classes. In almost all studies focusing on academic performance, the only difference in the online and traditional approach was the method of delivery of a lecture on the material. Traditional students viewed the lecture in person, while online students viewed videos of the lectures online. Navarro (2000), Figlio, Rush, and Yin (2010), Terry, Lever, and Macy (2003), and Howsen and Lile (2008) found that grades were significantly better in traditional lecture courses. However, Shoemaker and Navarro (2000) and Harmon and Lambrinos (2007) noted that online students' grades were significantly higher than those of students in traditional courses. Bennett et al (2007) found that microeconomics students' grades were higher in traditional classes, while online grades were higher for macroeconomics students. Finally Brown and Liedholm (2002), Bennett, McCarty, and Carter (2011), and McCarty, Bennett, and Carter (2013) reported no significant difference in the online and traditional student grades. However when the population was segmented by ethnicity, aptitude, and effort, Bennett, McCarty, and Carter (2011), and McCarty, Bennett, and Carter (2013) found that the grade gap between minority versus non-minority, high effort vs low effort, and high-aptitude vs low-aptitude students was greater in the online courses than in the traditional lecture courses.

Methodology and Results

Cerego is the adaptive learning platform used in this research. Cerego uses spaced repetition, where students are quizzed on terms and concepts, repeated at intervals over time to improve the learner's understanding and retention for longer periods of time. Cerego uses an artificial intelligence to determine which material is the most challenging for a particular student and quizzes the student on those questions more frequently in order to reinforce the topic for the student. Students are allowed to continue to new material to remain current with the text and lecture material if they have not reached the goal or competition level on a particular Cerego assignment. Until the end of the course, Cerego will continue to present the unmastered material until the student reaches the required goal level. Cerego defines levels of learning which measure the length that a student is likely to remember the material, with higher levels indicating longer periods of retention. Cerego levels range from 0.1- 4, with 0.1 meaning that the student will remember the material for a range of a days; 1, weeks; 2, months; 3, months to years; and 4, years.

The sample consists of 97 students enrolled in two hybrid sections of principles of microeconomics taught by the same instructor during the Spring 2019 semester. In addition to textbook material, the students were required to complete nine Cerego assignments that dealt with the topics being covered in their textbook and in class. In class each week, the students took a fifteen-minute, closed book and closed notes, written quiz on the previous week's material. Their quiz grade, which is used as the measure of student achievement, is the average of their best eight out of twelve in-class quizzes. The goal level set for Cerego was 1, which means that the student should retain the material for a period of weeks. The Cerego level variable is the average of the levels reached by the student on the nine assignments. The Cerego completion level is the percentage of the Cerego assignments that the student completed by achieving at least the goal level of one.

Table 1 summarizes the descriptive statistics for the students in the sample.

Table 1 Student Characteristics

Gender	
Female	58.8%
Male	41.2%
Ethnicity	
African American	21.6%
Caucasian	78.4%
Averages	
Quiz Grade	76.63 (17.18)
Cerego Completion Percentage	70.1 (37.86)
Cerego Level	0.82 (0.487)
GPA	3.23 (0.593)
ACT	23.1 (4.007)
Time (minutes)	502.5 (385.8)

Values in parentheses are standard deviations.

Almost 60% of the students were female, while approximately 40% were male. Almost 22% were African American, and 78% were Caucasian. The average grade on the in-class quizzes was 76.63. The average student completed 70.1% of the Cerego assignments and reached a level of 0.82. The average GPA was 3.23, and the average ACT was 23.1. Students spent an average of 502.5 minutes on their Cerego assignments.

Table 2 Student Characteristics by Gender

	Women n=57	**Men n=40**	**Significance (p-value)**
Quiz Grade	76.54 (17.03)	76.75 (17.61)	0.945
Cerego Completion	75.3 (36.07)	62.7 (39.56)	0.113
Cerego Level	0.879 (0.466)	0.725 (0.499)	0.132
GPA	3.31 (0.565)	3.10 (0.618)	0.096
ACT	22.79 (4.24)	23.58 (3.697)	0.332
Time (minutes)	523.6 (348.7)	406.4 (253.5)	0.058

When the students were separated by gender, we found virtually no difference in the quiz grade between women and men. Women completed a larger percentage of the Cerego assignments and reached a higher level than men, but the difference was not significantly different. The women's average ACT score was less than the average ACT score for men, but the difference was not statistically significant. Women had a statistically significant higher GPA and time spent on the Cerego lessons, which may indicate that they put forth more effort than the men in the sample.

Table 3 Student Characteristics by Ethnicity

	Caucasian n=76	African American n=21	Significance (p-value)
Quiz Grade	78.65 (16.876)	69.33 (16.671)	0.031
Cerego Completion	70.46% (37.114)	68.81% (41.384)	0.870
Cerego Level	0.832 (0.491)	0.757 (0.479)	0.535
ACT	24.14 (3.509)	19.38 (3.500)	0.000004
GPA	3.30 (0.568)	2.95 (0.621)	0.024
Time	472.1 (299.420)	486.7 (381.401)	0.872

In the subsamples based on ethnicity, the average quiz grade, ACT, and GPA for the Caucasian students were significantly higher than for African American students. There was no significant difference in the Cerego completion percentage or level or the time spent studying Cerego.

Assuming that the students' ACT scores are measures of their aptitude, we separated the sample into a high-aptitude group and a low-aptitude group. The median ACT score was 23, so we defined low aptitude as an ACT score less than or equal to 23. Students with ACT scores of 24 or more were assigned to the high aptitude group. Table 4 represents the descriptive statistics for the two groups.

Table 4 Student Characteristics by Aptitude

	Low Aptitude n=55	High Aptitude n=42	Significance (p-value)
Quiz Grade	71.9 (16.222)	82.8 (1.414)	0.002
Cerego Completion	62.8% (39.751)	79.6% (33.333)	0.026
Cerego Level	0.68 (0.953)	0.99 (0.219)	0.002
GPA	3.03 (0.271)	3.48 (0.005)	0.0001
Time	474.3 (348.042)	476.5 (298.072)	0.972
Female	61.8%	54.8%	0.485
African American	34.5%	4.76%	0.0001

The quiz grade, Cerego completion, Cerego level, and GPA were all significantly higher for the high-aptitude students. A significantly larger percentage of the low-aptitude students were African Americans. The quiz average for the African American students in the low-aptitude sample was 67.7, while the quiz average for the Caucasian students was 74.2, which was a statistically significant difference at the 8% level. Among the high-aptitude students, the African American students quiz average, 85, was slightly higher, but not statistically significantly higher, than that of the Caucasian students, 82.7.

We used regression analysis to determine the impact of the Cerego level, gender, ethnicity, ACT as a measure of aptitude, and the level of effort based on time spent studying Cerego. The quiz grade was used as the dependent variable. Gender and ethnicity, were dummy variables where 0=female and 1=male and 0=Caucasian and 1=African American. The results are shown in Table 5.

Table 5 Initial Regression Results

	Entire Sample n=97	Low Aptitude n=55	High Aptitude n=42	Caucasian n=76	African American n=21	Women n=57	Men n=40
Level	15.63 (0.000)	10.69 (0.140)	23.85 (0.000)	17.78 (0.001)	14.59 (0.113)	19.05 (0.001)	11.02 (0.217)
Time	-0.0044 (0.501)	-0.0022 (0.810)	-0.0018 (0.834)	-0.0005 (0.354)	-0.0083 (0.465)	-0.0052 (0.419)	-0.0032 (0.858)
Gender	1.36 (0.667)	1.69 (0.706)	4.31 (0.345)	3.59 (0.309)	-7.26 (0.347)		
Ethnicity	-4.06 (0.344)	-7.87 (0.092)	11.5 (0.259)			-1.76 (0.741)	-9.93 (0.234)
ACT	0.835 (0.093)			0.306 (0.607)	2.136 (0.042)	0.664 (0.270)	0.875 (0.379)
R-sq(adj)	25.25%	10.53%	35.11%	22.55%	22.94%	29.08%	18.30%

In the initial regression results for the entire sample, gender, ethnicity, and time spent on Cerego were not significant predictors of the quiz grade, but both the Cerego level and ACT score both had a significant, positive impact on the quiz grade. For the low-aptitude students the only significant variable was ethnicity, which had a negative effect on the quiz grade. The Cerego level had a significant positive effect for the high-aptitude students. The Cerego level had a significant positive effect for the Caucasian students and female students, and was positive, but not statistically significant for the African American students and the male students. The ACT score was significantly positive for only the African American students.

Forward stepwise regressions with alpha to enter of 0.25, displayed in Tables 6a - 6g, were performed to determine the variables that explained the most variation in the average quiz grades.

Table 6a Stepwise Regressions for Entire Sample (n=97)

	Step 1	Step 2
Level	16.27 (0.000)	13.33 (0.000)
ACT		1.175 (0.004)
Adjusted R^2	20.38%	26.50%

Values in parentheses are p-values.

Table 6b Stepwise Regressions for Low Aptitude Students (n=55)

	Step 1	Step 2
Level	8.02 (0.105)	9.31 (0.059
Ethnicity		-7.84 (0.087)
Adjusted R^2	4.87%	10.13%

Table 6c Stepwise Regressions for High Aptitude Students (n=47)

	Step 1	Step 2
Level	21.06 (0.000)	21.99 (0.000)
Ethnicity		11.42 (0.249)
Adjusted R^2	36.05%	36.64%

Table 6d Stepwise Regressions for Caucasian Students (n=76)

	Step 1	Step 2
Level	16.92 (0.000)	17.28 (0.000)
Gender		4.06 (0.242)
Adjusted R^2	23.15%	23.55%

Table 6e Stepwise Regressions for African American Students (n=21)

	Step 1	Step 2
ACT	1.99 (0.060)	2.294 (0.023)
Level		14.17 (0.051)
Adjusted R^2	13.10%	26.24%

Table 6f Stepwise Regressions for Women (n=57)

	Step 1	Step 2
Level	19.67 (0.000)	16.57 (0.000)
ACT		0.890 (0.071)
Adjusted R^2	27.70%	30.72%

Table 6g Stepwise Regressions for Men (n=40)

	Step 1	Step 2
Ethnicity	-16.87 (0.013)	-13.89 (0.036)
Level		10.60 (0.046)
Adjusted R^2	12.82%	19.75%

For the entire sample and the six sub-samples, the Cerego level had a significant positive effect on the average quiz grade. ACT score had a significant positive effect on the entire sample, African American students, and women. Ethnicity had a significant negative impact on the sample of low-aptitude students and men. The impact of the Cerego level was higher for the high-aptitude students than for the low-aptitude students.

Conclusion and Future Work

The Cerego level was consistently positive and significant for the entire sample as well as for the subsamples when students were separated according to aptitude as measured by the median ACT score, ethnicity, and gender. This suggests that the Cerego adaptive learning experience benefited students in general. The fact that the Cerego level coefficient was larger for the high-aptitude students may mean that the high-aptitude students benefitted more from Cerego. This result suggests that research to make adaptive learning more effective for low-aptitude students is necessary.

The results of this initial research on the use of adaptive learning in principles of microeconomics showed a positive impact of adaptive learning; however, the sample is relatively small, and the explanatory variables are limited. Future research should include a larger sample and other student characteristics, such as employment status, financial stress, class level, major, transfer status, and being a first-generation college student, as well as students' evaluation of the adaptive learning experience. It would also be beneficial to determine which student characteristics made them more likely to finish adaptive learning assignments. Finally, Cerego's primary strength and focus are on definitions and concepts, with less emphasis on analysis and critical thinking. There are many adaptive learning programs available in economics now that do focus on analysis and critical thinking, so further research should be conducted to measure the impact of these more advanced adaptive learning programs.

Security is another significant concern in any discussion of modern adaptive learning and certainly deserves review and much more research. The growing prevalence of all online learning necessitates an awareness of potential privacy and security issues for students and instructors and their institutions. Future research should be conducted in safe data usage control to reduce the risk of the unauthorized access to academic data. (Rajkumar and Sandhu, 2016; Rajkumar and Sandhu, 2020). In addition, research on developing appropriate security protection frameworks and protocols for online learning is necessary (Raghaven, Desai, and Rajkumar, 2017; Raghaven, Desai, and Rajkumar, 2020).

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