HOW DO STUDENTS USE ONLINE INTERACTIVE SOFTWARE? EVIDENCE FROM A PRINCIPLES OF MICROECONOMICS COURSE

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ABSTRACT

An increasing number of courses use some type of supplementary computer assisted software. There is mixed evidence supporting the effectiveness of this type of software in improving student learning. After laying out the monitoring tools available for instructors, this paper examines student usage of online resources in sections of a principles of microeconomics course. Although no direct link between exam scores and software usage was found, considerable variation in how students use the software was observed, and some of this variation can be related to student attributes such as GPA and gender.

Keywords: *Principles of Economics, Aplia, Mindtap, online homework*

INTRODUCTION

Textbook publishing companies continue to expand their offerings of automated homework software (Bojinova, 2012; Dolar, 2018). Some of these new tools allow instructors to track student activity during the academic term, using a variety of metrics. This paper takes advantage of a rich set of data to analyze how students at a regional comprehensive public university used the online resources in a principles of microeconomics course. This paper provides a description of the tools available for instructors to track student activity and then reports on how students used the software. Second, it explores how usage of the software related to student GPA, gender, classification, and major. Additionally, it provides an examination of how students used the opportunity to complete multiple attempts of the same question, how early students started homework assignments, and how this usage was related to student attributes and performance in the course. Finally, there is an exploration of how both homework grades and the time spent on assignments related to performance on a comprehensive final exam.

To preview the results, there is substantial variation in how students used the available software; some students spend considerable time accessing these resources, while others only log in immediately before an assignment is due and spend very little time completing assignments. On average, students spend more time completing the first attempt of a question, when given multiple attempts at the same concept. Additionally, higher cumulative GPA is related to more time spent completing homework using the software, and on average female students spend more time completing the online homework assignments than their male counterparts. On average, male students also started their homework assignments half a day later. Finally, once controlling for student specific attributes such as cumulative GPA and classification status, there is no evidence that final exam grades were related to either time or performance on online homework assignments.

LITERATURE REVIEW

Much of the research on the use of online homework systems has used an experimental approach, where students assigned to sections using a computer automated homework system were considered to be in the treatment group. Allgood, Walstad, and Siegfried (2015) noted that measuring the effectiveness of new teaching methods can be difficult for several well-understood reasons. These complications include non-random student assignment to treatment and control groups, and student grade targeting in response to new methods of instruction, whereby student reduce study time in response to effective teaching innovations (Allgood et al., 2015). Regardless of these difficulties, attempts have been made to assess the effectiveness of automated online software, with decidedly mixed results.

Collins, Deck, and McCrickard (2008) examined performance on final exams in principles of microeconomics courses at Bellarmine University after instructors adopted Aplia, an online automated homework system. They found that grades on the online assignments were positively related to final exam grades, at this small private university. Emerson and Mencken (2011) found that student grades on a common portion of a principles of microeconomics final exam were higher in sections that had graded Aplia assignments, as opposed to a control group where the assignments were not counted toward the course grade. Additionally, Nguyen and Trimarchi (2010) found statistically significantly higher grades in principles of economics course sections that used either Aplia or MyEconLab (Pearson's computer automated homework system), as compared to sections not using either of the software tools.

However, not all studies have found measurable benefits from using these types of software. Kennelly, Considine, and Flannery (2011) compared student scores on the Test of Understanding in College Economics (TUCE) in principles of economics sections using traditional hand-graded paper homework assignments versus sections using Aplia. They find no evidence of a difference in performance on the TUCE exam, for sections that used traditional instructor-graded paper assignments versus automated online homework. Also using the TUCE exam, Lee, Courtney, and Balassi (2010) found no improvement in scores after moving from traditional homework to Aplia, in a sample of principles of microeconomics courses. However, they do report that 90 percent of students reported that the software had a positive impact on their understanding of course material, and 73 percent of students reported preferring Aplia to traditional homework. Aljamal, Cader, Chiemeke, and Speece (2015) compare sections using Aplia to sections with no homework at all, in the American University in Kuwait. They find no difference in scores on the TUCE for sections using Aplia.

Additionally, some research has focused on specific elements of the software design, and how students respond to these elements. Rhodes and Sarbaum (2015) investigated how students responded to the option of completing multiple attempts in MyEconLab homework assignments. One proposed advantage of computer automated software is that students get instantaneous feedback on their mastery of the material and some software allows for them to make multiple attempts to apply the same type of problem (Parker & Loudon, 2012). There is a large literature suggesting that this type of formative assessment, where students receive feedback on their work throughout the learning process, can aid in student learning (Hattie & Timperley, 2007). Comparing two separate summer sessions, Rhodes and Sarbaum found evidence that when students are given multiple attempts at homework they guessed on the first attempt and tended to earn higher homework grades without increasing learning, as compared to the students only given one opportunity to answer questions. They noted that instructors need to be aware of students incentive to 'game the system' when designing their courses.

Caplan and Gilbert (2008) also studied student behavior, but instead focused on when students started Aplia assignments. In an intermediate microeconomics class, they find that students that started on the assignments earlier earned higher average scores on these assignments. Caplan and Gilbert controlled for student specific GPA and credits earned, and not only provided an early attempt at examining how students actually use the computer automated software but also showed how instructors can construct a database to study how students use this software.

However, as previously stated, most research has used an experimental approach, where the performance of students using the software is compared to a control group where the software is not used. Increasingly, software allows instructors to observe very detailed student-specific usage, and could provide insight into why the software may or may not increase student learning. For example, if students are not spending significant amounts of time engaging with the software, it would not be surprising if there are no measurable increases in student learning after adoption. Additionally, if students simply 'game' the assignments in their first attempts, the software may not lead to increased student learning and better performance on exams. It is also possible that software has heterogeneous effects on student performance; some students might benefit from the immediate feedback of the automated systems and the opportunity to work through multiple attempts, while other students may perform poorly if they discover that they can 'game the system' with very little effort put into the assignments.

BACKGROUND AND COURSE SETUP

The course sections under study are eight principles of microeconomics sections delivered by one instructor over the course of a two-year period in spring and fall semesters at a regional comprehensive public university in East Texas. Each section consisted of between 49 and 65 students, and met face-to-face either two or three times per-week for a total of 150 minutes per-week. Students took three regular in-class exams, and a cumulative final exam at the end of a 15 week semester. These exams were standard multiple choice tests taken on paper and with closed notes. No substantial changes to the course structure were made over this two-year period.

Students were required to purchase access to Mindtap, a supplementary online course tool developed by Cengage Learning.[1] Mindtap contains access to an online textbook, supplemental practice problems and chapter reviews, videos, flashcards, and required homework assignments. The course was set up so that students could access all available materials from the online software at any time, but that only eleven homework assignments would count toward their course grades. Students were given direct links to these assignments, in their course management system. The required homework assignments were based upon the Aplia software, an automated online homework system first developed by the economist Paul Romer in 2000,

[1] In fact, all instructors in the department require purchase of Mindtap in both principles of microeconomics and macroeconomics courses. In addition, a common text is used, so all sections have the exact same textbook/software requirements.

and available for use starting in 2002 (Kennelly et al., 2011). Aplia was later purchased by Cengage Learning in 2007.[2]

During the course of the term, students were assigned eleven graded assignments, with the top ten scores counting toward their final course grades. Overall, the graded homework assignments combined to be approximately 20 percent of the final course grade. The Aplia homework assignments were specifically tailored for the chosen textbook, and the assignments were designed so students worked through interactive microeconomics problems. A typical assignment required students to fill in the blanks for terms, complete calculations on a microeconomic concept, and construct and/or manipulate graphs. Once satisfied with their responses, students could submit the problem and receive instantaneous feedback about their answers. This feedback not only showed the student which questions they got right and wrong, but provided a detailed explanation for each of the problems. Subsequently, students could choose to 'try another version' of a slightly different problem on the same concept. In this way, the software allowed for a formative assessment for the student, and immediate feedback without the need of any interaction from the instructor. Students had a maximum of three attempts for each of the problems within each assignment. The students' grades were based on the highest score from the maximum of the three attempts of each problem.

According to Cengage Learning, the Mindtap software tracked student activity using Google Analytics and other tools, although certain user-installed browser extensions can block this tracking (Cengage, 2019).[3] Cengage notes that these browser extensions could possibly bias downward actual student usage, although it is unclear why a particular student would only sometimes use one of these browser extensions. Additionally, because Mindtap and Aplia were originally two separate software systems, they track user progress in the course in slightly different ways. Mindtap activity could be associated with students using a variety of learning tools, including the online textbook, chapter reviews, flashcards, etc., whereas time spent on Aplia assignments will only correspond to the time spent on the graded homework assignments.

DATA DESCRIPTION

In total, 459 students enrolled in these eight sections during this two-year period. In order to only track student behavior of students engaged throughout the entire semester, 46 students were removed from the sample because they either withdrew from the course or did not take the final exam. Additionally, one student was removed from the sample because no data was collected about login activity, likely because of the use of an ad-blocking browser extension. Summary statistics are available in Table 1 for the remaining 412 students in the sample. After receiving IRB exemption, student specific characteristic were merged with information about student software usage.

In terms of student profile, the typical principles of microeconomics student is a full-time sophomore business major, with slightly more than 50 percent of the students being male. From Table 1 it is clear that there was substantial variation in how extensively students accessed the

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[2] This purchase did lead to some confusion for students. Students completed Aplia assignments on the Mindtap platform, which was developed and sold to them by Cengage Learning.

[3] One student in the two-year period likely used one of these browser extensions, as Mindtap collected no information about her login behavior, even though she had recorded grades for each assignment.

Mindtap system. On average students spent approximately 21 hours in Mindtap during the term, and logged in a few times per week. However, some students spent substantially more time logged into the system, with one student recording 130 hours of time in Mindtap during the 15 week term. It should be noted that approximately 10 percent of the students initially enrolled in the course either withdrew or stopped attending during the term, which has substantially affected some of the averages in Table 1. For example, the exam and assignment grade averages, number of logins, and minutes spent in Mindtap would all be lower if these excluded students were added to the sample. These students are excluded to give representation of time spent during an entire term of usage.

Table 1
DESCRIPTIVE STATISTICS FROM MINDTAP

	Observations	Mean	Std. Dev.	Median	Min	Max
Minutes in Mindtap	412	1258.30	929.33	1047	49	7945
Number of logins	412	35.09	17.24	32	6	144
Aplia #1 grade	412	78.18	28.01	89.08	0	100
Aplia #2 grade	412	86.38	24.76	95.17	0	100
Aplia #3 grade	412	74.79	26.83	83.50	0	100
Aplia #4 grade	412	86.66	27.65	98.05	0	100
Aplia #5 grade	412	80.64	25.23	88.83	0	100
Aplia #6 grade	412	79.43	29.19	91.67	0	100
Aplia #7 grade	412	75.75	29.75	86.83	0	100
Aplia #8 grade	412	68.33	30.14	79.67	0	100
Aplia #9 grade	412	77.52	31.90	91.75	0	100
Aplia #10 grade	412	77.70	31.91	91.02	0	100
Aplia #11 grade	412	77.91	31.04	89.67	0	100
Regular exams	412	72.86	13.37	73.54	36.67	100
Final exam	412	71.40	13.97	72.37	27.63	97.37
Cumulative GPA	412	2.90	0.66	2.90	0.43	4.00
Credits in term	412	13.17	2.35	13.00	6	19
Male (yes=1)	412	0.56			0	1
Freshman (yes=1)	412	0.10			0	1
Sophomore (yes=1)	412	0.58			0	1
Junior (yes=1)	412	0.24			0	1
Senior (yes=1)	412	0.08			0	1
Business major (yes=1)	412	0.86			0	1

Table 2 presents a correlation matrix for selected variables. For simplicity of presentation, homework assignments are averaged by student into one *homework total* variable.

Interestingly, scores on Aplia assignments were positively correlated with exam performance, but time spent in the Mindtap software as measured by *mindtap minutes* and *number of logins* were not strongly related to scores on exams. The strongest correlations were exam scores. Students' performance on regular exams were positively related to their scores on the cumulative final exam. Unsurprisingly a student's cumulative GPA was also highly correlated with exam performance.

Table 2
CORRELATION COEFFICIENTS OF SELECTED VARIABLES

	Mindtap minutes	Logins	Homework total	Regular Exam	Final Exam	Cum. GPA	Credits	Male	Aplia first*
Mindtap minutes	1.00								
Logins	0.64	1.00							
Homework total	0.26	0.23	1.00						
Regular Exam	-0.11	-0.05	0.44	1.00					
Final Exam	-0.07	-0.05	0.44	0.81	1.00				
Cum. GPA	0.03	0.04	0.62	0.75	0.73	1.00			
Credits	-0.04	0.02	0.11	0.16	0.15	0.18	1.00		
Male	-0.19	-0.11	-0.13	-0.03	-0.04	-0.22	0.02	1.00	
Aplia first*	0.71	0.26	0.47	0.17	0.19	0.28	0.07	-0.19	1.00
Aplia multiple*	0.56	0.25	0.38	-0.09	-0.02	0.07	0.00	-0.26	0.52

*These correlations are only measured for the second of the two years, as described below.

As previously mentioned, because Aplia and Mindtap were originally two separate software systems, they collect slightly different data on student usage. One shortcoming of using Mindtap's tracking time and login information is that one cannot observe what tools students are using in the software. To add an additional complication, an unknown number of students either purchased a physical copy of the textbook or downloaded an offline version of the textbook to their phone or tablet using an application provided by Cengage. Some variation in Mindtap access time could be due to the different ways students accessed the textbook, because some students use Mindtap to access the text and other do not. However, the eleven Aplia homework assignments could only be completed online and the software collected very detailed information about student activity on these assignments. Unfortunately, only the second of the two years of data was available in Aplia, for a total of 210 students. Aplia tracked information about when students first accessed each graded homework assignment and how much time they spent on every single portion of each Aplia assignment.

The last two rows of Table 2 provide correlations for the time spent on the first and subsequent (multiple) attempts on the homework assignments, and Table 3 provides some of the summary statistics for this second source of student access data. The total time in minutes spent on graded Aplia homework assignments is *Aplia first* plus *Aplia multiple*, while *non-Aplia time* is any remaining minutes spent in Mindtap not related to the graded Mindtap assignments, for this subset of 210 students. As with the Mindtap data, there is substantial variation by student.

On average, students spend more time on the first attempt than on the additional attempts allowed by the homework system. There is substantial variation, as one student spent no time at all on additional attempts, while others spent more time on these multiple attempts than other students spent on all available activities in the entire Mindtap system. From an instructor's perspective, one concern with adopting a homework system with multiple attempts is that students might spend little time on the first attempt and only use this attempt to reveal the answers to the question. Students could then mimic the answer from the first attempt to maximize scores on the remaining two attempts, without actually engaging with the concept. At least in this sample, students spend more time on average on the first attempt, which suggests that most students are not 'gaming the system' in this way.

Aplia also allows for instructors to track when students log in to each homework assignment. The various *start* variables correspond to number of days before the deadline at which students first accessed the graded homework assignment. On average, students tended to first open the graded homework assignments a few days before each was due. Some students waited until only minutes before the assignment was due to first open the assignment, and some students never opened assignments, as the number of observations for each assignment is less than 210, which is the number of students finishing the course during these two terms. It should be noted that a handful of students worked ahead substantially, with one student starting the last assignment more than two months before its due date. Although not included in Table 3, exam scores, Aplia scores, and student characteristics are similar in this one-year sub-sample, as compared to the full two-year sample as described in Table 1.

Table 3
ADDITIONAL DESCRIPTIVE STATISTICS FROM APLIA

	Observations	Mean	Median	Std. Dev.	Min	Max
Aplia first	210	396.89	361.97	197.81	44.37175	1294.82
Aplia multiple	210	142.95	121.36	100.45	0	637.16
Non-Aplia time	210	654.90	500.22	587.81	54.82	4741.70
Start average	210	2.33	1.88	2.40	0.05	28.96
Start Aplia 1	195	2.71	1.52	2.71	0.00	12.05
Start Aplia 2	198	2.18	1.35	2.24	0.03	11.25
Start Aplia 3	190	2.25	1.36	2.09	0.01	11.29
Start Aplia 4	196	3.49	2.15	3.63	0.02	22.31
Start Aplia 5	193	1.68	1.11	2.09	0.02	15.15
Start Aplia 6	188	1.87	1.10	2.65	0.00	22.30
Start Aplia 7	185	1.89	1.04	3.14	0.01	24.01
Start Aplia 8	197	2.16	1.39	4.20	0.01	51.27
Start Aplia 9	184	2.87	1.14	4.50	0.01	43.01
Start Aplia 10	181	2.09	1.05	3.87	0.00	34.41
Start Aplia 11	187	3.40	2.04	6.61	0.02	78.08

DETERMINANTS OF STUDENT SOFTWARE USAGE

As previously mentioned, there is substantial variation in how students in the sample used the software. To investigate what factors are related to student time spent using the software, several linear regressions were estimated, with the dependent variables being various measures of software usage. Because there are a handful of students with substantially above average time spent using the software, the dependent variables are transformed using the natural log function to reduce the impact of these outliers. Table 4 presents the results of these regressions, for both the full two-year sample and the subset of data where more detailed Aplia usage was available. Columns 1 and 2 display the results of models of Mindtap access as a function of student specific characteristics. The only statistically significant coefficient from these first models is gender; as compared to female students, males logged on to Mindtap less frequently and for less total time during the semester. Again, estimating time spent on the Mindtap system is made more difficult because of it is unknown if some students accessed the textbook outside of the software.

Table 4
REGRESSION RESULTS FOR SOFTWARE USAGE

	(1)	(2)	(3)	(4)	(5)
Variables	ln(Mindtap minutes)	ln(Logins)	ln(Aplia first)	ln(Aplia multiple)	ln(Average Start)
Cum. GPA	0.0833	0.0594	0.241***	0.206**	0.434***
	(0.0620)	(0.0444)	(0.0670)	(0.103)	(0.0920)
Credits	-0.0140	0.00523	0.0141	0.0126	0.0184
	(0.0140)	(0.0107)	(0.0153)	(0.0218)	(0.0220)
Male (yes=1)	-0.233***	-0.0771*	-0.159**	-0.419***	-0.168
	(0.0686)	(0.0465)	(0.0690)	(0.106)	(0.114)
Freshman (yes=1)	0.112	0.0441	-0.0425	-0.220	-0.0846
	(0.106)	(0.0785)	(0.103)	(0.189)	(0.144)
Junior (yes=1)	-0.0128	0.0546	0.0862	0.0889	0.0771
	(0.0825)	(0.0553)	(0.0864)	(0.143)	(0.132)
Senior (yes=1)	0.0680	-0.0588	-0.0154	-0.0901	0.0455
	(0.141)	(0.0837)	(0.175)	(0.197)	(0.219)
Business (yes=1)	0.0389	-0.0087	0.0319	0.0460	0.2630*
	(0.0956)	(0.0604)	(0.0980)	(0.158)	(0.159)
Constant	6.951***	3.250***	5.029***	4.162***	-1.100***
	(0.248)	(0.190)	(0.289)	(0.415)	(0.393)
Observations	412	412	210	209†	210
R-squared	0.048	0.023	0.136	0.117	0.159

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
† One student did not make any attempts beyond the first.

Columns 3-5 display the results of estimated linear regressions related to Aplia homework access. The dependent variable of interest are respectively the natural log of total minutes spent on the first attempt on all homework assignments in Aplia, minutes spent on additional homework attempts, and average time before the deadline when the student started the homework. Using R-squared as a guide, these models explain more of the variation in student access to only the Aplia homework than the models estimating Mindtap access. Additionally, for this sample, a student's cumulative GPA is estimated to be related to Aplia homework access. With at least 95 percent confidence, it is estimated that students with higher GPAs spent more time on their homework attempts and started the assignments earlier, on average. As with Mindtap access, female students are estimated to have spent more time on the online homework, on average. In no models is there evidence that class status, number of credits taken during the term, or whether the student was a business major was related to software usage, at normal levels of statistical significance.

RELATIONSHIP OF SOFTWARE USAGE TO EXAM GRADES

One final area of investigation is the link between exam performance and software usage. Table 5 contains the results of linear regressions with the dependent variable measuring percentage score on a comprehensive final exam. Models in columns 1 and 3 estimate final exam scores based upon student characteristics, but without independent variables related to software usage. Column 1 represents the full two-year sample, while column 3 only includes the subset of students with available information on Aplia usage. Unsurprisingly, students with higher cumulative GPAs are estimated to have higher average scores on the final exam. There is also some evidence that, all else equal, freshman score slightly lower than sophomores, which is the classification dummy variable that was dropped for comparison. Males are estimated to have higher final exam scores in the model, but careful interpretation must be used to interpret this finding. In fact, females have higher exam scores overall in the sample, on average. However, they also have higher cumulative GPAs, which is strongly related to exam scores. Once correcting for GPA and other characteristics, a male student with the same GPA and other characteristics would be estimated to have a slightly higher final exam score.

Columns 2, 4, and 5 display estimates for models that include various measures of student software usage. *homework total* is a student's online homework average, and the other additional variables are the previously described software access variables. None of these variable coefficients are statistically different than zero, with the exception of the number of logins to Mindtap. Somewhat counterintuitively, an increase in logins is estimated to be negatively correlated to a lower final exam score, on average, although the addition of software usage variables add very little explanation of variation in final exam scores. There is a substantial literature in educational psychology that suggests that spaced learning, or small amounts of regular time spent learning, contributes to more learning that a few long study sessions (Kang, 2016). Unfortunately, Mindtap does not report whether the logins are spaced out, or whether multiple logins are occurring over short durations of time. It is possible that many of these logins are occurring right before an exam.

Recall from Table 2, there was some positive correlation between *homework total* and exam scores. However, once one controls for GPA, there is no estimated relationship between Aplia homework scores and final exam grades. One interpretation of this finding is that high GPA students exert more effort on their homework, this effort helps them to learn the material, and they therefore do better on exams. However, it is difficult to disentangle the direction of causality. A high GPA student may simply find the homework easier to do and it does not help to increase understanding of the topic. An additional interpretation of the results is that once one knows a student's GPA, the time spent on homework is redundant in explaining her performance on exams.

Table 5
REGRESSION RESULTS FOR FINAL EXAM GRADES

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Final exam	Final exam	Final exam	Final exam	Final exam
Homework total		-0.0121		-0.0766	-0.0772
		(0.0441)		(0.0755)	(0.0769)
ln(Mindtap minutes)		0.0609			
		(0.800)			
ln(Mindtap logins)		-2.635**			
		(1.109)			
ln(Aplia first)				0.693	0.704
				(1.822)	(1.844)
ln(Aplia multiple)				0.398	0.398
				(1.285)	(1.288)
ln(Average Start)					0.0265
					(0.191)
Cum. GPA	15.96***	16.31***	16.92***	18.16***	18.15***
	(0.873)	(0.957)	(1.236)	(1.182)	(1.182)
Credits	0.0772	0.0926	-0.166	-0.151	-0.152
	(0.175)	(0.179)	(0.239)	(0.243)	(0.245)
Male (yes=1)	3.570***	3.386***	3.557***	3.605***	3.625***
	(0.890)	(0.922)	(1.192)	(1.343)	(1.388)
Freshman (yes=1)	-3.211**	-3.149*	-4.512***	-4.761***	-4.746***
	(1.623)	(1.630)	(1.603)	(1.658)	(1.659)
Junior (yes=1)	-0.292	-0.143	-0.994	-0.936	-0.933
	(1.128)	(1.137)	(1.626)	(1.563)	(1.571)
Senior (yes=1)	0.0292	-0.175	1.448	0.904	0.902
	(1.956)	(1.865)	(2.812)	(2.812)	(2.823)
Business (yes=1)	0.519	0.506	-1.953	-2.136	-2.148
	(1.259)	(1.249)	(1.752)	(1.753)	(1.763)
Constant	22.07***	30.56***	26.24***	22.57**	22.55**
	(3.425)	(6.197)	(4.791)	(8.988)	(9.038)
Observations	412	412	210	209†	209†
R-squared	0.560	0.568	0.600	0.613	0.613

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
† One student did not make any attempts beyond the first.

CONCLUSION

This paper has shown how instructors can track students' automated software usage, and has also linked this usage to student characteristics and performance on exams for a sample of students in a principles of microeconomics course. In this sample, substantial variation exists in the amount of time students spent engaging with the software. Although final exam grades do not appear to be related to software usage once other factors are controlled for in this sample, there are clear and systematic differences in student usage of the software. Specifically, female students spend more time on the assignments, and there is a positive relationship between GPA and both time spent on homework and how early students begin assignments, on average. Unfortunately, the sample size of this study is too small to further narrow the detailed student access behavior at a more disaggregated level.

This study falls into the broad area of 'learning analytics', a concepts defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environment in which it occurs" (Leitner, Khalil, & Ebner, 2017). There are several potential avenues for using data from automated homework systems to make changes in the learning environment to improve student learning. Ideally, instructors may be able to identify students that are not sufficiently engaged in the course material. Currently, Cengage provides total time and number of logins to Mindtap as the key element of measurement of student engagement for instructors. Unfortunately, because of the offline mechanisms available for students to access the textbook, these measures may not be the most accurate in determining actual student engagement. Metrics from Aplia, such as the time spent on various homework attempts, have not been made easy for instructors to access. However, these metrics may be more useful in understanding student engagement. In the future, software creators may wish to consider making detailed student access data more easily viewable for instructors.

Additionally, future work could link specific assignments to specific concepts on exams, to isolate which assignments are most linked to important content areas of the course. As publishing companies continue to collect 'big data' on student behavior, it may be possible to more carefully study the link between homework system usage and student learning over large samples of students. The literature on the efficacy of these types of software has been mixed. However, by examining detailed student usage of the software, instructors can now study how students use the software in very fine-grained detail. Understanding student behavior at this detail may be the key to determining whether software improves student learning. If students are spending very little time engaged with the software it would be unsurprising if there was no associated increase in student learning. Perhaps there is heterogeneity in effectiveness of assignments, and only some of the assignments are related to improvement in student learning. There may even be heterogeneity in effectiveness of software among students. Additionally, some systems may be 'gamed' by students looking to maximize grades with minimum effort. Resolving these issues may be the key to determining whether the software is effective.

As previously mentioned, there is some evidence that providing students feedback on their progress during a course can promote student learning (Hattie & Timperley, 2007). This type of continuous feedback has traditionally been very costly, in terms of instructor time. As an increasing number of courses use some sort of supplementary computer assisted software to provide students instantaneous input on their work. Engagement information can be provided directly to students either by the software or instructor. Students may be unaware of the amount of time that they need to spend on homework and placing their usage in context may be helpful. Additionally, the software could be more fully personalized for each student, and could be designed to provide different assessments for each student, depending upon the specific needs of that individual student.

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