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Board 324: Is Adaptive Learning for Pre-Class Preparation Impactful in a Flipped STEM Classroom?

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Abstract

Adaptive learning supports online learning by providing individualized learning paths, assessing students in real-time, and providing instant feedback or suggestions using AI algorithms. As part of a three-year NSF-funded study, the project team implemented adaptive learning in a flipped numerical methods course for pre-class preparation, using multiple previous semesters of flipped classroom data as the benchmark. Assessment data from 330 students was collected at three diverse engineering schools using a final exam (i.e., for direct knowledge assessment) and the College and University Classroom Environment Inventory (CUCEI) for student perspectives. Although some differences in the direct assessment measures with the use of the adaptive lessons were seen based on the particular school, the overall effects of the adaptive lessons were small, negative, and non-significant. The classroom environment results were more favorable for adaptive learning, with four of the seven environmental dimensions having notable positive effect sizes. In this article, we present information on the development and implementation of adaptive lessons in the RealizeIT adaptive platform as well as assessment outcomes by school and for the schools combined.

1. Introduction

Flipped instruction offers the potential for enhanced learning *during class* by enabling problem-solving and other types of active learning. However, active learning is dependent on sufficient pre-class preparation. This challenge motivated the present research, in which we aimed to support pre-class preparation through personalized, AI-driven adaptive learning.

Adaptive learning delivers customized content, administers assessment with immediate feedback, and allows self-paced learning (Daugherty et al., 2022; Munoz et al., 2022). Our NSF research implemented adaptive learning using the RealizeIT platform (https://www.realizeitlearning.com) in an undergraduate numerical methods course at three engineering schools - a large southeastern public university, a large southwestern public university, and a small, southern public HBCU (NSF Award No. 2013271, *Transforming Undergraduate Engineering Education through Adaptive Learning and Student Data Analytics*). Students were from mechanical, civil, and electrical engineering majors. We compared direct knowledge outcomes and student perspectives with and without adaptive lessons in the flipped classroom.

2. Related Literature

Given differences in students' knowledge and understanding, adaptive learning platforms can be used to provide content, resources, and customized learning paths to offer personalized learning at scale (Munoz et al., 2022). Daugherty et al.'s recent literature review identified the increasing popularity of adaptive learning and the need for more research to better establish its direct connection to improved learning (Daugherty et al., 2022). Another systematic review identified the increasing popularity of adaptive learning technology alongside few empirical research studies on it (Munoz et al., 2022). As an example of an implementation, adaptive learning courseware was developed for a large introductory political science course using the RealizeIT platform (Brown et al., 2022). With their direct assessments, they found a (modest) 4% difference in common exam questions between the adaptive and non-adaptive sections, with the adaptive section performing better (Brown et al., 2022).

3. Methods

3.1 Development of Adaptive Lessons

The instructors from the three universities began the development of the adaptive lessons in the Summer 2020 and finished at the end of the Fall 2020 semester. Due to previous NSF grants, one of the instructors had previously developed online content for the numerical methods course, which could be re-used for the adaptive platform content. Thus, a large percentage of the adaptive lessons, particularly the videos and textbook content, existed through previously funded work (Kaw et al., 2012; Kaw & Garapati, 2011; Owens et al., 2012).

The numerical methods course consists of eight topics, and each topic was subdivided into objectives within the RealizeIT platform used in this study. The course topics include differentiation, nonlinear equations, simultaneous linear equations, interpolation, regression, integration, and ordinary differential equations (ODEs), in addition to an introduction to scientific computing. A total of 30 objectives were developed within the platform. Each objective was further divided into individual lessons, known as nodes, for a total of 121 nodes. For example, under the course topic of differentiation, and for the objective of differentiation of continuous functions, the two nodes were entitled "first derivative" and "second derivative." Each node or lesson consists of five sections - overview/introduction, learning objectives, videos, textbook content, and assessment questions. For the assessment, a pool of questions was developed. The video, textbook, and other content are freely available online (Numerical Methods Guy, 2023; Kaw & Nguyen, 2023).

3.2 Implementation of Adaptive Lessons

At the southeastern university (i.e., University of South Florida, USF), the adaptive lessons were implemented in the Fall 2021 and Spring 2022 semesters. At the southwestern university (i.e., Arizona State University, ASU), the lessons were implemented in the Fall 2023. At the HBCU (i.e., Alabama A&M University, AAMU), they were implemented in the Spring 2023. The flipped classroom *without* the adaptive lessons was implemented at the southeastern university during Fall 2014 and Fall 2015, at the southwestern university in Spring 2023, and at the HBCU in Spring 2016. This is summarized in Table 1. The larger time difference between the treatments (at two of the universities) occurred because of the two separate NSF grants involved. However, the instructors remained the same for these two universities over time. For the other university, a new instructor had to be recruited unexpectedly during the second (adaptive learning) grant; therefore, the semesters involved at this school were much closer in time.

By way of example, at the southeastern university, each objective was made available on a Thursday and was due 11 days later before the class period. The 11-day period allowed students two weekends to learn the material and complete the assessments. If a lesson was a prerequisite to another lesson, the student had to receive a minimum score of 59% to progress. To discourage guessing, incorrect attempts reduced the score for the objective. The in-class exercises then were based on the content of the adaptive lessons. Problem sets were assigned after class but not graded.

3.3 Student Participants

The number of participants at each university, including as a percentage of the course enrollment is given in Table 1. A student was considered to be participating if the student opted into the study and provided both demographic and final exam data, with the demographic data collected via a survey. The participation rates in the study were between 75% and 85%, depending on the semester and school. Using the demographic survey, students were asked to indicate the grades they had received in the prerequisite courses (i.e., calculus, differential equations, linear algebra, programming methods, and physics). These grades were used to compute a prerequisite GPA for each student, which was then used as a control variable when statistically analyzing their exam scores for the two treatment conditions.

Table 1: Study Participants

University	Student Participants	Flipped	Flipped w/ Adaptive
Southeastern University (USF)	# participants (as % of enrolled) terms enrolled	88 (75%) fall14, fall15	117 (84%) fall21, spring22
Southwestern University (ASU)	# participants (as % of enrolled) terms enrolled	41 (79%) spring23	41 (77%) fall23
HBCU (AAMU)	# participants (as % of enrolled) terms enrolled	23 (85%) spring16	21 (81%) spring23

3.4 Assessment Methods

3.4.1 Direct Assessment

The final exam, which remained exactly the same throughout the entire study for all schools and instructors, served as the direct assessment measure. It has a multiple-choice portion with 14 questions and a free-response portion with four questions. The multiple-choice questions measured the lower-level skills in Bloom's taxonomy, and the free-response questions assessed the higher-level skills in the taxonomy (Felder & Brent, 2016).

The final exam scores for the two treatments were compared statistically using an analysis of covariance (ANCOVA), with the prerequisite GPA serving as the covariate (Norusis, 2005). This comparison was made by the school and for the schools combined. Since the sample sizes for the HBCU were not large, the non-parametric version of ANCOVA - Quade's test - was also run with the HBCU data (Quade, 1967; Lawson, 1983). The Bonferroni correction was applied, given that multiple tests were conducted across the schools (Perneger, 1998; Bland & Altman, 1995). Cohen's *d* effect sizes were calculated to measure the practical significance of the differences, with $d = 0.20$ considered small, $d = 0.50$ considered medium, and $d = 0.80$ being large (Lakens, 2013; Sullivan & Feinn, 2012; Cohen, 1988).

3.4.2 Classroom Environment Inventory

The College and University Classroom Environment Inventory (CUCEI) was used to assess the classroom environment for both treatment conditions (Fraser & Treagust, 1986). This validated inventory contains seven classroom dimensions - cohesiveness, individualization, innovation, involvement, personalization, satisfaction, and task orientation. Several of these dimensions are particularly applicable to the flipped classroom or to adaptive learning. For example, personalization (i.e., interaction with the instructor) is a key objective with flipped instruction. Individualization (i.e., students treated individually or differentially) is a crucial objective of adaptive learning. These seven psychosocial dimensions were compared between the two treatment conditions as simultaneous outcomes using multiple analysis of variance, or MANOVA (Field, 2005). The Bonferroni correction was applied given the seven simultaneous tests. Cohen's *d* effect sizes were calculated for each dimension.

4. Results

4.1 Direct Assessment Results

The multiple-choice and free-response scores from the final exam were each compared for the flipped version of the course with the lessons versus the flipped version without the adaptive lessons. The results in Table 2 are for each school individually as well as for the three schools combined. In examining the results at USF, there was actually a medium, statistically significant negative effect with the adaptive lessons ($d = -0.66$). At USF, however, the adaptive lessons were implemented in the fall 2021 semester, the first fully in-person semester after the COVID-19 pandemic. The instructor surmised that this may have been a factor in lower student performance. The adaptive lessons were also implemented at USF immediately following this in Spring 2022. At ASU, there was a negligible difference between the two treatments, which were both implemented after the pandemic due to the change in instructor from the original flipped classroom study. Conversely, at AAMU, an HBCU, there was a large increase in the multiple-choice results with the adaptive lessons ($d = 1.68$), with $p < 0.001$ for both the parametric ANCOVA and Quade's (non-parametric) tests. Thus, it is possible that the adaptive lessons may have been particularly supportive or helpful to these URM students. Upon combining the data from the three schools, the overall effect associated with the adaptive lessons for the multiple-choice responses was small and non-significant ($d = -0.13$).

Table 2: Multiple Choice Comparison: Flip vs. Flip with Adaptive Lessons

School	Adjusted Mean Percentage % (s_{adj}) n Flip	Flip + Adaptive	Parametric ANCOVA *p*	Effect Size *d*
Combined	55.4 (19.1) 152	52.9 (19.1) 179	0.237	-0.13
USF	66.7 (17.1) 88	55.7 (17.0) 117	<0.001	-0.66
ASU	41.9 (16.4) 41	41.9 (16.4) 41	0.998	0.00
AAMU	34.4 (16.0) 23	61.0 (16.0) 21	<0.001 <0.001 (Quade's)	1.68

For the free-response questions, there was a small positive effect associated with the adaptive lessons at ASU ($d = 0.20$), as shown in Table 3. At USF, however, there was a very small, non-significant negative effect with the adaptive lessons ($d = -0.05$). The free-response questions were not administered at AAMU due to unplanned circumstances. Upon combining the data from the schools, the overall effect of the adaptive lessons for the free response questions was also small and non-significant ($d = -0.08$).

Table 3: Free Response Comparison: Flip vs. Flip with Adaptive Lessons

School	Adjusted Mean Percentage % (s_{adj}) n Flip	Flip + Adaptive	Parametric ANCOVA *p*	Effect Size *d*
Combined	46.1 (23.4) 152	44.2 (23.4) 158	0.495	-0.08
USF	40.0 (21.7) 88	38.8 (21.6) 117	0.705	-0.05
ASU	55.9 (19.0) 41	59.6 (19.0) 41	0.376	0.20

4.2 Classroom Environment Inventory Results

Upon combining the classroom environment data for the three schools, there were four classroom environment dimensions with notable positive effect sizes in favor of adaptive learning. The largest effect was for the Task Orientation dimension ($d = 0.41$), with the Bonferonni-adjusted *p*-value of $p_{adj} < 0.007$, as given in Table 4. This dimension relates to organization and clarity of activities. For example, *Activities in this class are clearly and carefully planned*. This positive effect aligns with the nature of adaptive lessons, particularly the organization of the online resources and assessments. The second largest classroom environment effect with the adaptive lessons was Satisfaction (d = 0.36; p_{adj} = 0.007). Thus, the adaptive lessons may be associated with enhanced student satisfaction, such as *The students look forward to coming to classes*. The Individualization dimension did *not* exhibit a shift with adaptive learning, as expected (d = -0.01). This dimension relates to individual and differential treatment, which is a key goal of adaptive learning. However, several of the questions for this dimension relate to self-pacing, which occurs with flipped instruction in general. Nonetheless, adaptive learning was associated with an enhanced classroom environment in this study.

Table 4: Classroom Environment Comparison: Flip vs. Flip with Adaptive Lessons

Dim	**Mean** (s)		**Univariate *p***	**Univariate *p* (adjusted)**	**Effect Size *d***
	Flip	**Flip + Adaptive**			
Coh	2.95 (0.88)	2.93 (0.79)	0.89	1.00	-0.02
Indiv	2.72 (0.75)	2.71 (0.62)	0.90	1.00	-0.01
Inn	2.90 (0.59)	2.94 (0.63)	0.54	1.00	0.07
Invol	3.23 (0.65)	3.41 (0.61)	0.012	0.084	0.28
Pers	3.88 (0.79)	4.11 (0.61)	0.003	0.021	0.33
Satis	3.07 (1.03)	3.43 (0.96)	0.001	0.007	0.36
Task Or	3.73 (0.69)	4.01 (0.63)	<0.001	<0.007	0.41
n	152	177			

Coh = Cohesiveness (Students know & help one another)
Indiv = Individualization (Students treated individually/differentially & can make decisions)
Inn = Innovation (Novel class activities or teaching techniques)
Invol = Involvement (Active student participation in class activities)
Pers = Personalization (Interaction w/ instructor & concern for student welfare)
Satis = Satisfaction (Enjoyment of classes)
Task Or = Task orientation (Organization and clarity of class activities)
Note: Flip was considered the reference category for this analysis.

5. Summary and Conclusions

In our previous NSF grants with the flipped classroom, we observed insufficient pre-class preparation for the in-class active learning component. Therefore, this three-year study focused on the use of adaptive learning in the RealizeIT platform for pre-class preparation for a flipped, numerical methods engineering course. Although the direct-assessment data as a whole (i.e., combined) was associated with small, non-significant effects with the adaptive learning, the adaptive lessons may have contributed to enhanced performance for URM students at the HBCU.

The classroom environment outcomes were more favorable with the adaptive lessons versus without them. Four of the classroom environment dimensions had notable positive effect sizes with adaptive learning, in particular, the Task Orientation dimension, which measures the organization and clarity of class activities. This effect may be a general result with adaptive learning. Future publications will present results from the full study, which is to be completed in the spring 2024 semester. Although adaptive learning was implemented in a flipped classroom for this study, it can be implemented in a traditional classroom as well for material reinforcement and review or for other goals the instructor may have.

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References

Bland, J., & Altman, D. (1995). Multiple significance tests: The Bonferroni method. *BMJ, 310(6973),* 170.

Brown, C., Grussendorf, J., Shea, M., & DeMas, C. (2022). Changing the paradigm? Creating an adaptive course to improve student engagement and outcomes in introductory political science classes. *Journal of Political Science Education*, *18*(3), 301-326. https://doi.org/10.1080/15512169.2022.2069573

Clark, R., Kaw, A., Lou, Y., Scott, A., & Besterfield-Sacre, M. (2018). Evaluating Blended and Flipped Instruction in Numerical Methods at Multiple Engineering Schools. *International Journal for the Scholarship of Teaching and Learning, 12*(1), Article 11. https://files.eric.ed.gov/fulltext/EJ1172254.pdf

Clark, R., Besterfield-Sacre, M., Budny, D., Bursic, K., Clark, W., Norman, B., Parker, R., Patzer, J., & Slaughter, W. (2016). Flipping Engineering Courses: A School Wide Initiative. *Advances in Engineering Education*, *5*(3), 1-39.

Cohen, J. (1988). *Statistical power analysis for the social sciences*. Lawrence Earlbaum Associates.

Daugherty, K., Morse, R., Schmauder, A., Hoshaw, J., & Taylor, J. (2022). Adjusting the future of adaptive learning technologies via a SWOT analysis. *Intersection: A Journal at the Intersection of Assessment and Learning*, *3*(2), n2.

Felder, R. & Brent, R. (2016). *Teaching and learning STEM*. San Francisco, CA: Jossey-Bass, 31.

Field, A. (2005). *Discovering statistics using SPSS.* London: SAGE Publications, 571-618.

Fraser, B., & Treagust, D. (1986). Validity and use of an instrument for assessing classroom psychosocial environment in higher education. *Higher Education*, *15*, 37-57.

Kaw, A., Yalcin, A., Clark, R., Braga Gomes, R., Serrano, L., Scott, A., & Lou, Y. (2024). On Building and Implementing Adaptive Learning Platform Lessons for Pre-Class Learning in a Flipped Course. *ASEE Computers in Education*, (in print).

Kaw, A. & Nguyen, D. (2024). *Numerical methods with applications: unabridged*. https://nm.mathforcollege.com/NumericalMethodsTextbookUnabridged/

Kaw, A., Yalcin, A., Nguyen, D., Pendyala, R., Hess, M., Lee-Thomas, G., Besterfield, G., Eison, J., & Owens, C. (2012). A holistic view on history, development, assessment, and future of an open courseware in numerical methods. *ASEE Computers in Education Journal*, *3*(4), 57-71.

Kaw, A. & Garapati, S. (2011). Development and assessment of digital audiovisual YouTube lectures for an engineering course in numerical methods. *ASEE Computers in Education Journal*, *2*(2), 89-97.

Lawson, A. (1983). Rank analysis of covariance: alternative approaches. *The Statistician*, *32*(3), 331-337.

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 863.

Muñoz, J., Ojeda, F., Jurado, D., Peña, P., Carranza, C., Berríos, H., Molina, S., Farfan, A., Arias-Gonzales, J., & Vasquez-Pauca, M. (2022). Systematic review of adaptive learning technology for learning in higher education. *Eurasian Journal of Educational Research*, *98*(98), 221-233.

Norusis, M. (2005). *SPSS 14.0 statistical procedures companion*. Upper Saddle River, NJ: Prentice-Hall, 183, 457-459, 545-549, 563-567.

Numerical Methods Guy, Retrieved March 13, 2024, from https://www.youtube.com/numericalmethodsguy

Owens, C., Kaw, A., & Hess, M. (2012). Assessing online resources for an engineering course. *Computer Applications in Engineering Education*, *20*(3), 426-433. https://doi.org/10.1002/cae.20410

Perneger, T. (1998). What's wrong with Bonferroni adjustments? *BMJ, 316*(7139), 1236-1238.

Quade, D. (1967). Rank analysis of covariance. *Journal of the American Statistical Association, 62*(320), 1187-1200.

RealizeIt: Adaptive Learning Platform. (n.d), Retrieved March 13, 2024, from https://www.realizeitlearning.com/

Sullivan, G., & Feinn, R. (2012). Using effect size-Or why the p value is not enough. *Journal of Graduate Medical Education, 4*(3), 279-282. https://doi.org/10.4300/JGME-D-12-00156.1