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Autar Kaw
University of South Florida, kaw@usf.edu

Renee Clark
University of Pittsburgh

Eleonora Delgado
University of South Florida

Nicholas Abate
University of South Florida

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Autar Kaw ORCID iD: 0000-0002-3976-6375

Analyzing the use of adaptive learning in a flipped classroom for pre-class learning

Autar Kaw, Department of Mechanical Engineering, University of South Florida, Tampa, FL kaw@usf.edu

Renee Clark, Engineering Education Research Center, Swanson School of Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania rmclark@pitt.edu

Eleonora Delgado, Department of Mechanical Engineering, University of South Florida, Tampa, FL, edelgado2@mail.usf.edu

Nicholas Abate, Department of Mechanical Engineering, University of South Florida, Tampa, FL, nabate@mail.usf.edu

ABSTRACT

Pre-class learning, an obstacle in the success of a flipped classroom, is addressed via placing lessons on an online adaptive platform. The lessons combine the power of video lectures, textbook content, simulations, and assessments while using personalized paths for each student. This article describes the development of the adaptive lessons for a course in Numerical Methods, and the interpretation of the analytic data collected via the adaptive lesson platform and student focus groups over a two-semester period with 146 students. Analytical data includes student metrics such as the lesson scores and the time spent and lesson metrics such as the percentage of students who completed the lesson and the percentage of possible adaptive paths used by students. The focus groups were conducted for two different demographic groups – students who are “white males” (comprise the majority of students in public engineering schools in the USA) and “other than white males” – to compare their perspectives on adaptive learning. Students in the focus group of the “other than white male” pupils demonstrated more favorable and positive perspectives towards the adaptive learning compared to the “white males”, although both groups identified benefits with the adaptive platform. Final examination scores were found to be correlated with the raw score of the adaptive lessons.

Keywords: Adaptive learning, numerical methods, flipped classrooms, active learning, data mining

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1. Introduction

Active learning, where students are engaged with the content by participating in class and collaborating with their peers to construct knowledge, develop metacognition skills, and improve understanding of the material, is associated with improved student performance in science, technology, engineering, and mathematics (STEM) courses. As per the classic meta-study conducted by Freeman, et al., an effect size (defined roughly as the ratio of the difference between the means of the treatment group and the control group, and dividing it by the standard deviation of one of the groups) of medium level of 0.47 was observed in classes with active learning when compared with traditional classes [1]. Students were also 1.5 times more likely to fail in a traditional class than an active one [1].

One of the ways to introduce active learning is through the flipped classroom [2]. This involves students getting their first exposure to the course content via textbook readings and lecture videos. To provide proper incentive to the students, an online quiz through a learning management system offered by the school or the textbook publisher may be taken by students. Others give a quiz in the beginning of the class session. Pre-class quizzes allow the instructor to judge what topics students are struggling with and hence create activities that help students during the class meeting time.

The in-class activities for students in a flipped classroom may include answering conceptual questions, solving procedural problems, and outlining a project [3]. These can be guided by the instructor and teaching assistants through micro lectures and solving the in-class problems with their assistance. Alternatively or additionally, peer instruction [4, 5] can be implemented where the students attend mini-lectures and then answer conceptual questions. These questions are anonymously answered using personal response systems such as clickers [6], followed by pairing students when questions are not answered correctly by more than say 25% of the students and sharing of their thinking with the class. This technique is called think-pair-share (TPS) [7, 8]. Ideally, the TPS activity should be followed by the instructor going through the question and its distractors for a complete discussion, hence avoiding any misconceptions.

In a Numerical Methods course at the University of South Florida, the flipped classroom did not show a statistical or pragmatic difference over the blended classroom [3]. However, more than half of the students pointed out the advantages of flipped classes, such as problem-solving, availability of instructor and TAs to help, and learning from their peers. At the same time, one of the points of resistance [9] in the flipped classroom is getting the students to do the pre-class learning. To overcome this resistance, we hypothesized that if we replaced the current one-size-fits-all approach to pre-class preparation by a personalized pathway through adaptive learning [10], we could improve the cognitive and affective performance of students. Adaptive learning is defined as the tailored delivery of content, feedback, and assessment via computers that account for the unique needs of each individual.

This paper hence describes the development of the adaptive lessons, the interpretation of the resulting metrics collected via the adaptive platform, and how they were related to the performance and perspectives of students in a Numerical Methods course.

2. Literature review

The classical paper by Freeman, et al. [1], a definitive meta-study, showed that active learning was associated with enhanced performance in STEM classes over the traditional lecture by 6%. Active learning refers to activities that engage students during class time with their peers and instructors, while not requiring one to abandon the lecture. Examples include simple techniques such as the one-minute paper, think-pair-share, and personal response systems to complex techniques such as problem-based learning, inquiry methods, and experiential learning.

One of the ways to incorporate active learning in the classroom is to implement the flipped learning approach. This method is defined as “a pedagogical approach in which direct instruction moves from the group learning space to the individual learning space, and the resulting group space is transformed into a

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dynamic, interactive learning environment where the educator guides students as they apply concepts and engage creatively in the subject matter." [2]

Although the idea of flipped learning has been around for centuries, it was King [11] who first described a shift in teaching from teacher-centered to student-centered. In higher education, the first instance is claimed to be in 2000 by Lage, Platt, and Tregilia, who wrote a paper "Inverting the Classroom: A Gateway to Creating an Inclusive Learning Environment" [12] based on the changes they made to their introductory economics class. They moved the classroom lecture to outside of the classroom via media such as lecture videos, PowerPoint presentations, and textbook readings. In turn, the class time was used to process and apply principles of economics through short lectures and student discussion. In 2007, Kaw and Hess [13] compared four instructional modalities (self-study, traditional, flipped, and blended, although termed differently in their paper) for a single topic (i.e., nonlinear equations) for a course in Numerical Methods. They found that the flipped classroom had the largest effect size (d=0.57) for the related questions on the final examination, while from an affective-domain perspective, the blended technique was the best. Since then, numerous studies have been conducted in STEM courses to compare the flipped classroom with the traditional lecture. A review of flipped classes in engineering was done by Bishop and Verleger [14] in 2013. Their survey analysis included full and partial flips, as well as single group and controlled group studies. They suggested that further research should be conducted with control groups, and comparisons should be based on concept inventory as well as procedural examinations.

Then in 2016, in a special issue of the ASEE AEE journal, eight papers were published on flipped classrooms [15]. Results were mixed when comparing students' learning, confidence, and conceptual learning in flipped classrooms versus traditional ones. The editors suggested that guidance should be provided on how to design individual activities, and instructors should be able to observe student behaviors in the learning process [16]. Given the mixed results, the editors also raised the following question: "Do students indeed learn more in active learning environments, such as blended and flipped classrooms? To definitively answer this question, we need to find out what kinds of active learning work best, when, in what context, and why, through studies with adequate statistical power that report effect sizes."

In the most recent literature review in 2018 [17] of research on flipped classrooms in engineering education that spanned 62 papers, it was concluded that students in flipped classrooms learn as much as in the traditional lectures. They also found that evaluation methods were limited to quantitative data and that there is a need for qualitative research data as well. They suggested that flipped classrooms should be based on a theoretical framework, and the validity and reliability of the assessment instruments should be addressed as well.

Although the flipped classroom has been found to be effective in many cases, two challenges remain. First is the one-size-fits-all approach for the pre-class learning. For example, an instructor may assign a few short videos or a few pages of the textbook reading. To ensure that the content preparation is adequate for classroom activities, the instructor may give an online quiz or an in-class quiz at the beginning of the class. Second is student resistance to the pre-class activity that stems [10] from two reasons: 1) expectations of student ownership of learning are higher in flipped classrooms [18], and 2) prior knowledge that may be inactive (e.g., pre-requisites taken a while ago), insufficient (e.g., students transferring from different colleges), inappropriate, or inaccurate, which hinders learning [19]. To combat both of these challenges, we replaced the pre-class learning with adaptive lessons. These lessons combined the various media while taking students on personalized paths to learning the material via instant feedback and self-paced learning, and if needed, a review of pre-requisite material.

Ever since one-on-one tutoring has existed, adaptive learning has been successful in improving the performance of students [20]. Modern adaptive learning finds its roots in the 1950s. It was Cronbach [21] in 1957 who used student attributes to seek differentiation in instruction. Although his results were mixed, it seeded the current adaptive learning initiatives. It started with rule-based systems in the 1970s, which were soon replaced by intelligent tutoring systems. These systems tried to replicate the human tutoring experience in the 1980s [22] but could not match the claimed effect size of d=2 over conventional classes, as described in Bloom's 1984 seminal paper [23] of "The 2 Sigma Problem". However, in a 2011 meta-

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study by VanLehn [20], the actual effect size of human tutoring was found to be *d*=0.8, which is comparable to those of intelligent tutoring systems [22] of the 1980s. These systems were followed by adaptive hypermedia systems, as they included hypertext and adaptivity [24]. In the 21st century, several commercial adaptive learning platforms (ALPs) such as Knewton [25], Smart Sparrow [26], and Desire2Learn [27] have evolved wherein the adaptive platforms use a multitude of statistics, machine learning, predictive analytics, psychometrics, etc. to improve the lessons.

A meta-analysis on adaptive learning conducted by SRI reported data on 23 courses over three years, 19,500 students, and 280 instructors [28]. Adaptive learning was not shown to improve passing rates in these cases. However, in other instances, student success has been found to improve. Georgia State reduced the DFW (students who drop, fail or withdraw from the course) rate in college algebra from 43% to 21% [29]. This study included 7,500 students, of which 56% were Pell grant recipients, 60% were non-white, and 30% were first-generation college students. At ASU, the DFW rate was reduced from 16% to 7% in developmental mathematics courses with 2,000 students [30]. Adaptive learning has also been reported to improve engagement, identify at-risk students, and increase student retention [31-33].

In this work, we incorporated adaptive learning to improve pre-class learning in a flipped classroom. We chose to use the Smart Sparrow platform [26], as it is content-agnostic, it permits various forms of content and assessments, and it allows the instructor to develop the adaptive lessons free of charge, while students pay a nominal fee to use the lessons. The platform provides raw and inferred data for the instructor to modify the lessons and conduct interventions for higher impact. The scores were automatically transferred to grading systems of the major learning management systems such as Blackboard and Canvas.

In this paper, we discuss the development of the adaptive lessons, followed by the interpretation of the ALP student metrics, including hours spent on lessons and the percentage of students who completed each lesson. Content analysis of the qualitative data from two demographically-diverse focus groups via coding are also presented to describe various student perspectives on the adaptive learning. The focus group questions included those related to impact, satisfaction, and engagement with the adaptive learning platform. Our research questions were as follows:

1) What are the relationships between use of an adaptive platform and subsequent exam performance?

2) What types of student performance metrics are available from an adaptive platform, and what useful information do they provide to an instructor?

3) What are students' perspectives, including key benefits and drawbacks, on the use of an adaptive platform in a STEM course? Do these perspectives differ by particular demographic groups?

3. Development of Lessons

The lessons were developed for the pre-class work for a flipped classroom in a Numerical Methods course. A typical Numerical Methods course consists of the following eight topics:

1. Introduction to Scientific Computing
2. Differentiation
3. **Nonlinear Equations**
4. **Simultaneous Linear Equations**
5. Interpolation

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6. **Regression**

7. **Integration**

8. Ordinary Differential Equations

Since the work was funded by a limited exploratory grant [34], the lessons were developed for only half of the course topics. The topics chosen for the development are the ones in **bold** in the above list. These were the topics in which the students struggled the most as measured by the final examinations given in previous semesters. We developed 17 lessons for the four topics and implemented them during two semesters at the University of South Florida in an undergraduate numerical methods course for mechanical engineers.

The lessons were developed on the adaptive learning platform of Smart Sparrow. A lesson is made up of a series of screens with varying content that the student is directed to based on their interaction and performance. The ALP included video lectures, textbook content, simulations, and assessments in the form of multiple-choice, algorithmic, and fill-in-the-blank questions, among others. HTML 5 and JavaScript were used for developing the simulations. The interactions with the adaptive lesson could include how much time the student spent on the screen, a button clicked, or a typed input. These interactions were tracked using variables, which could then be used in various “Correct States” or “Trap States” (incorrect states) that dictate the progression of the lesson for each individual student. These variables were used to calculate the score for the lesson.

A typical adaptive lesson would start with the objectives of the lesson followed by showing a lecture video on the theory of a numerical method followed by multiple-choice questions. Two attempts were given for the question, and if any of them were not answered correctly within these attempts, related textbook content was shown and multiple-choice questions were asked again. Following the same philosophy, a video on an example of the numerical method was shown and followed then by algorithmic questions. Two attempts were given, and if the questions were not answered correctly, textbook content was shown, followed by the same algorithmic questions. If the questions were not answered correctly, the user was sent to the pre-requisite module. Depending on whether the student was able to answer the questions correctly or not, previous algorithmic questions were asked again with two attempts. This ended the lesson. A student could retake the lesson as many times as desired. A flow chart for a typical lesson is shown in Figure 1. Typical content and assessment elements are shown in Figure 2, using the Newton Raphson method for solving nonlinear equations as an example.

4. Adaptive Learning Platform Analytics

A valuable aspect of an adaptive platform is the capability to collect data on students’ use of and behavior with the platform for formative and instructional purposes. A sample of these data metrics is discussed in the paper to demonstrate the types of decision support available to the instructor with an adaptive platform such as Smart Sparrow. The instructor routinely examined various metrics at both the student and lesson levels, including the following:

Student Metrics

- Number of attempts to successfully complete the lesson (i.e., answer all questions correctly)
- Raw lesson score (i.e. score on all questions asked in all attempts)
- Actual lesson score (i.e., after final attempt)
- Hours spent on lesson
- Hours the lesson was completed before due date

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Lesson Metrics

- Percentage of students who completed the lesson
- Custom states used (as a percentage of maximum states)

Several of the student metrics were also aggregated so they could be examined at the lesson level, such as median or average number of attempts for the lesson, median or average raw and actual score for the lesson, median or average hours spent on the lesson, and median or average hours the lesson was completed before the due date.

5. RESULTS: COGNITIVE AND ADAPTIVE ANALYTICS

The flipped classroom without adaptive learning had 88 participants (out of 121 registered students) from the semesters of Fall 2014 and Fall 2015, while the flipped classroom with adaptive learning had 146 participants (out of 194 registered students) from the semesters of Fall 2017 and Spring 2018. All registered students in the class were taught using the two learning options in the above respective semesters and 25.8% of these registered students did not participate in the study by declining or neglecting to give consent, or by dropping or withdrawing from the course. No data from non-participants were used in the reported results.

5.1. Final Examination

Identical final examinations were given for the two treatments of the flipped classroom with and without the adaptive learning. The final examination consisted of two parts - 14 multiple-choice questions and 4 free response questions, and the two parts were weighted equally. The difference in the students' average performance with the two treatments was not statistically significant as determined by the p-value (probability for a given statistical model that when the null hypothesis is true), and the effect size was small, as shown in Table 1. More detailed comparisons based on final examinations (cognitive learning) and a classroom environment survey (affective learning) of these two treatments as well that with blended learning are given in a separate paper [35].

5.2 Smart Sparrow Analytics

Relationships between Smart Sparrow Analytics and Final Exam Performance

Correlations were calculated between percentage achieved on the final exam (for the topics that were covered in Smart Sparrow) and the student's adaptive platform performance to determine or confirm anticipated relationships between their use of Smart Sparrow and their ultimate performance in the course. As shown in Table 2, the correlation between the final exam score and the raw score for all lessons was of medium size (r = 0.350) and significantly different from zero (p < 0.0005). This was a desirable finding because it indicated to the instructor that students' diligence with the Smart Sparrow content, as demonstrated by good first-time performance on the Smart Sparrow quiz questions, was subsequently associated with good performance on the final exam. The correlation between final exam performance and the actual score across all lessons after trying multiple times was small (r = 0.138, p=0.131). As expected, there was an inverse relationship between final exam score and total attempts to complete the lesson that was not quite significantly different from zero (r = -0.173; p = 0.057). There was almost no relationship between the final exam score and the total hours spent on the lesson (r = -0.003, p=0.972).

Metric: Lesson Completion

One of the metrics that an instructor has access to in Smart Sparrow is the percentage of students who completed the lesson successfully by going through the whole lesson. These completion percentages are shown in Table 3, and the minimum in the fall 2017 semester was 72.5% (for LU Decomposition). In the spring 2018 term, 81.4% was the minimum (for Discrete Data Integration). A large contributor to these

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high percentages was the fact that the adaptive lessons represented 10% of the student's grade, so students were externally motivated to complete them.

Metric: Adaptive States Utilized

One of the Smart Sparrow metrics of particular use to the instructor is the percent of custom states within a lesson triggered and used by at least one student in the class. A custom state is an adaptive feedback item provided to the student on a point of misunderstanding. The percent of states used is a way to measure the quality of the lesson's adaptivity to the students' performance, with 80% being considered by Smart Sparrow as a minimum threshold. The instructor can use this metric to make needed or desirable changes within a lesson to make it more responsive to student actions (i.e., more effectively target student responses).

For example, for the Trapezoidal Rule, the percentage of custom states utilized was 100% for both semesters as shown in Table 4. This utilization represents an ideal situation relative to adaptiveness. However, several of the lessons in Table 4 were pre-requisite lessons. For example, the definition of matrices, binary operations on matrices, setting up problems in matrix form, and the inverse of a square matrix are pre-requisites for Gaussian elimination and LU decomposition. For those lessons, which had lower percentages of states used, the students most likely completed them without difficulty and "breezed through" since they were pre-requisites. For the topics of partial derivatives, simple statistics, and finding the minimum of a function, although these were pre-requisite topics for regression, they did *not* have video lectures associated with them. The lack of video lectures combined with the low number of possible states likely led to students having more difficulty with these particular pre-requisite topics.

In analyzing these percentages, the instructor identified four lessons as candidates for rework to enhance their adaptiveness. Specifically, based on the percentages in Table 4, he determined that improvements should be made to the Bisection Method, Newton Raphson Method, Adequacy of Linear Regression Models, and Discrete Data Integration lessons, given percentages of less than 80%.

Metric: Lesson Completion Proactivity

On average, with the outliers removed, students completed the lessons hours ahead of the due date, although there was variability in the data based on the large standard deviations shown in Table 5. The minimum for each semester is shown at the bottom of Table 5. The assignments were released weekly on Thursdays at 5 PM (coinciding with the end time of recitation sessions) and were due the following Tuesday at 11:30 AM (one hour before the beginning of recitation sessions of the current week). The first two lessons show unusually large mean hours of completion before the deadline because during the Fall 2017 semester, we had to postpone the lesson deadline due to a weather emergency. Figure 3 shows a histogram for the lesson completion proactivity for a typical lesson.

Metric: Time Spent on Lesson

Table 6 shows the time spent on each lesson, and Figure 4 shows the histogram for a typical lesson. Although there was almost no correlation between time spent and the final examination score, these numbers are important as they illustrate the student effort invested before coming to the classroom. Any lesson that requires too much time can be adjusted accordingly. This also gives a more accurate picture of how much time students were spending on a lesson versus self-reported numbers, [36-39] which can be highly speculative.

Metric: Raw Lesson Score

As shown in Table 2, the raw score in the adaptive lessons was positively correlated (r = 0.350) with the exam performance of the students. The raw score takes into account the student's first-time performance on the quiz questions. The raw score is defined as the ratio of the points earned for all correctly-answered questions and the points available across all attempts. For example, assume three multiple-choice questions

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are shown to the student, and he/she gets no questions correct until the 4th time. At the 4th time, if the student gets two questions correct, his/her raw score at that point would be 2/12 or 16.67%. Table 7 shows the raw score for each lesson, while Figure 5 shows the histogram of the raw score for a typical lesson. This leads us to conclude that the lessons were designed properly, as students struggled but eventually achieved a median lesson score of 100%.

Other Metrics

The other metrics of number of attempts to complete the lesson and the actual lesson score (after the final attempt) did not provide additional insight. The median number of attempts for all lessons was one, with very few students making multiple attempts or no attempts at a lesson. The reason was that students were able to earn a full score within four rounds of one attempt. The median actual score for every lesson, if attempted, was 100% across both semesters, as students could go through the lesson multiple times, although the lesson completion rate by lessons ranged from 72% to 96% (Table 3).

6. rESULTS: STUDENT PERSPECTIVES

6.1 Focus Groups

Two focus groups per semester in the adaptive-learning classroom were conducted with students from each of the following two demographic groups: 1) white males (i.e., the majority group in engineering), and 2) students who were other-than-white-males. This was done to gather student perspectives on the adaptive learning and to examine potential differences in perspectives based on demographic background. A sample of the focus group questions is shown in Table 8.

For questions 1 through 3 in Table 8, the responses were coded in one of three possible ways – 1) positive, 2) negative, or 3) mixed/neutral. *Mixed/neutral* responses typically consisted of a combination of positive and negative statements or contained statements that were neutral or unclear. For question 4, the responses were coded in one of three ways also – 1) No difference, 2) Learning of Smart Sparrow topics better/Smart Sparrow preferred, or 3) Learning of Smart Sparrow topics *not* better/Smart Sparrow *not* preferred. In addition, for all of the questions (1-4), the content of the response was coded, with multiple content codes possible per response. These content codes explained or supported the student's perspective on the question. The coding scheme with these content codes is shown in Table 9.

The assessment analyst for the project (i.e., the second author) and an upper-level undergraduate student performed a content analysis of the qualitative data from the focus groups. After the coding schemes were developed by reviewing all the responses, each analyst independently coded the data, which they later discussed to ensure consensus on the final assigned codes. Thus, the data were double-coded. The first-time inter-rater reliability associated with the qualitative content data from the focus groups (i.e., a coding scheme in Table 9) was Cohen's $\kappa = 0.779$, showing strong agreement beyond chance [40]. Cohen's κ measures inter-rater agreement for qualitative items, where $\kappa=1$ represents complete agreement and $\kappa=0$ represents no agreement other than by chance. The first-time inter-rater reliability for the coding of responses as either positive, negative, or mixed/neutral (i.e., questions 1-3 in Table 8) was Cohen's $\kappa = 0.835$, showing strong agreement. Finally, for the responses coded as learning of Smart Sparrow topics better, learning of Smart Sparrow topics *not* better, or no difference (i.e., question 4 in Table 8), Cohen's $\kappa = 0.949$, again showing strong agreement.

6.2 Focus Group Results

During the fall 2017 and spring 2018 adaptive-learning flipped classrooms, out of the 146 study participants, a total of 20 students participated in the four focus groups over the two semesters. Of these 20 students, 11 students were white males, who represent the majority among engineering students, and 9 students were other than white males (females and underrepresented minorities such as African Americans, American Indians, and Hispanics) and this group will be referred to as the "other-than-white-males" group going forward.

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The proportion of the two groups represents the makeup of the 146 participants for the adaptive treatment as it consisted of 54% white males. Also, the focus groups were kept within a certain number of participants so that everyone has the opportunity to share insights while maintaining diversity of perceptions [41]. A prescribed range of participants for a focus group is 4 to 12 [41]. Given that 4 total focus groups were conducted, 20 students (total) are within this recommended range. Focus groups provide qualitative data, which was summarized using descriptive statistics, versus via inferential statistics.

The focus groups were selected as follows. Three one-hour windows toward the end of the semester were chosen for maximum participation by the evaluator (second author) and the instructor (first author) for students to sign up for the meeting times for the focus group. Students could choose any number of the one-hour options. The window that received the most responses was chosen as the meeting time for the focus groups and no volunteers were excluded. The meeting was conducted by the evaluator and an incentive of a $30 gift certificate was given to the focus group participants.

Below are the results from several of the focus group questions, in which responses from the two demographic groups are compared. These results demonstrate more favorable perspectives on adaptive learning by the other-than-white-males group.

Question 1: ***Did the Smart Sparrow adaptive platform impact your learning or understanding more so than other methods for studying, learning, or reviewing content? Why do you feel this was the case?***

The other-than-white-males had a more positive (and less negative) perspective towards their learning with the adaptive platform versus the white males, with four *positive* and just one *negative* response out of nine students to this question, as shown in Table 10. Conversely, the white males had three *positive* and four *negative* responses to the question out of 11 students. All remaining responses for both groups were classified as *mixed/neutral*. The percentages of positive and negative responses in Table 7 were calculated by dividing the number of each type of response by a number of focus group participants. Since some of the responses were mixed/neutral, or not all participants may have responded to a particular question, the percentages for each group do not necessarily sum to 100%. There were also cases in which a particular response was irrelevant to the question and was therefore not coded.

The (more-positive) other-than-white-males most frequently explained that the category of lecture preparation, content understanding, and increased accountability with the material (MAT PREP) was the adaptive-learning feature that was helpful to their learning (7 responses). This was followed by the presence of quiz questions (QUIZ QUES), whereby they could confirm, reinforce, or gain understanding (4 responses). In comparison, in the white-males group, these two categories were discussed in just 5 and 2 responses, respectively. The white males were critical of the feedback provided by the adaptive platform, stating a lack of detailed feedback or solutions in the case of incorrect answers (4 responses; NOT CLEAR) as well as the insensitivity of the feedback to small differences between the provided and expected answers (1 response; INACC FEED). Although some students perceived this insensitivity, each non-integer response was nonetheless acceptable to +/- 0.01. The other-than-white-males (in comparison) did not cite these issues at all. One other-than-white-male student said, *"Smart Sparrow did impact learning more than the typical approach. I had to pay attention and take notes when watching the video, and it helped me to understand better. I liked watching a video and then answering a set of questions right away."* Another other-than-white-male stated, *"I went over the material earlier and so would have to re-learn it later, which helped me. So, I had several times of being exposed to the same material…"*

Question 2: ***Discuss your satisfaction with the Smart Sparrow adaptive software and the reasons for it.***

Similarly, the other-than-white-males expressed greater satisfaction (and less dissatisfaction) with the adaptive software than the white males did. For the other-than-white-males, 5 responses were coded as positive, versus just one for the white males, as shown in Table 11 (i.e., 56% vs. 9% positive responses, respectively). Conversely, the responses coded as negative for these two groups totaled 2 and 5, respectively (i.e., 22% vs. 45% negative responses, respectively). The remainder for both groups were mixed/neutral responses.

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In describing their satisfaction, the other-than-white-males discussed the convenience of and guided approach of the adaptive platform, including the availability of all resources from the same website, the ability to work at one's own pace, and the capability to re-watch videos and re-work questions as many times as needed or desired (4 responses; CONVENIENCE). In contrast, the white males noted this "convenience" category in just 2 responses. In his interview, the instructor felt the availability of all resources from a single location was an advantage for the students. With the white males, although they discussed the category of lecture preparation, content understanding, and accountability (3 responses; MAT PREP), they also discussed dissatisfaction with the lack of detail present in the feedback offered by the platform (4 responses; NOT CLEAR) as well as a perceived lack of convenient or ready access to lessons or questions (8 responses; ACCESS). In particular, they were dissatisfied that the adaptive-platform questions were not available for re-answering until the video had been viewed again.

Question 3: ***Did the Smart Sparrow adaptive learning software impact your engagement with the course material?***

For the other-than-white-males, five (5) responses to this question about Smart Sparrow's impact on engagement were coded as *positive* responses, with just one response coded as *negative*. For the white males, although six responses were coded as *positive*, and three responses were coded as *negative*. These results are shown in Table 12, in which the percentage of positive responses was approximately the same for both groups, although the white males tended to be more negative based on their percentage of negative responses.

The other-than-white-males discussed the convenience of the adaptive platform (4 responses; CONVENIENCE) and the benefit of the quiz questions (2 responses; QUIZ QUES) in relation to their engagement. For example, one other-than-white-male student stated, *"I have 5 classes/lectures all in one day, and so it's easy for me to doze off in class. The adaptive lessons are nice because I can do them on my own time, which has impacted my engagement positively."* The white males discussed the category of lecture preparation, content understanding, and accountability as important to their engagement (6 responses; MAT PREP), although having to re-watch videos before re-answering questions did not contribute to engagement (1 response; ACCESS). For example, a more-engaged white-male student stated, "*I was more engaged during class because I knew what was going on."* However, another less-engaged white-male stated, "*It was frustrating at times when I got an answer wrong and then had to re-watch the videos. It lowered my enthusiasm when I had to go through the videos again. Have some supplemental questions (without required videos) that we can have access to also. This would make for more enthusiasm."*

Question 4: ***Compare and contrast your learning of the topics covered by Smart Sparrow versus those not covered by Smart Sparrow.***

For the other-than-white-males, six (6) responses were coded as "learning of Smart Sparrow topics better/Smart Sparrow preferred," with only one coded as "learning of Smart Sparrow topics *not* better/Smart Sparrow *not* preferred." The category of lecture preparation, content understanding, and accountability was discussed most frequently by the other-than-white-males in explaining their positions on this question (4 responses; MAT PREP). For example, one of these students explained, *"We recently went over ordinary differential equations (ODEs) - first, second, and higher order. I feel less prepared for the upcoming exam versus earlier exams that covered the Smart Sparrow topics. I will have to spend time outside of class studying. I would have more confidence if ODEs had been covered in Smart Sparrow. With Smart Sparrow, I was 'walked through' the material, could see my grasp of the material, and received a reward, which was nice, but I didn't have this with ODEs."*

For the white males, four (4) responses were coded as "learning of Smart Sparrow topics better/Smart Sparrow preferred," but four (4) responses were coded as "no difference" with regards to Smart Sparrow use. The white males also cited the category of lecture preparation, content understanding, and accountability most frequently in describing their positions on this question (5 responses; MAT PREP). These results are presented in Table 13. The other-than-white-males (compared to the white males) stated

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with a relatively greater frequency that their learning of the course topics within Smart Sparrow was better and/or they preferred the Smart Sparrow adaptive platform. Conversely, the white males (compared to the other-than-white-males) stated with a relatively greater frequency that there was no difference in their learning with the adaptive lessons. As stated previously, not all participants may have responded to a particular question; therefore, the percentages for each group will not necessarily sum to 100%.

CONCLUSIONS

In this work, adaptive lessons were used to conduct the pre-class learning for the flipped classroom as a way to enhance this aspect of the pedagogy, with the ultimate goal of improving cognitive and affective student outcomes. At one university (i.e., the University of South Florida), in comparing final exam scores in the flipped classroom with and without adaptive learning in our exploratory research grant, a small effect size was found for adaptive learning in the flipped classroom. However, the correlation was sizeable (r=0.35; p<0.0005) between the final examination score involving the topics available in Smart Sparrow and the raw score on the Smart Sparrow quiz questions, which took into account students' first-time performance. There were small correlations between the final exam score and other metrics, including the number of attempts and actual lesson score, with almost no correlation between exam score and time spent on the lessons.

Various metrics available from Smart Sparrow's analytics were detailed for each lesson to illustrate the decision support available to the instructor in implementing and utilizing the adaptive platform. This data, such as time spent, raw lesson score, and lesson completion percentages, described students' behavior with the platform and can be used formatively to adjust instructional practices and lesson features. A focus group was conducted to gather student perspectives on the adaptive learning, and these perspectives were compared between two demographic groups - white males (i.e., the majority group in engineering) and students who were other-than-white-males. The students in the latter group generally had more favorable and positive perspectives towards the adaptive software. Some of the most frequently-discussed advantages of the adaptive platform included lecture preparation, content understanding, and increased accountability with the material (MAT PREP). In addition, the convenience of and guided approach of the adaptive platform, including the availability of all resources from the same website, the ability to work at one's own pace, and the capability to re-watch videos and re-work questions as many times as needed or desired was also frequently mentioned by the students during the focus groups (CONVENIENCE).

The results from this exploratory research study of adaptive learning in the flipped STEM classroom have shown promising results, both in terms of cognitive and of affective student outcomes. Therefore, we hope to expand this exploratory work via a research grant with additional engineering schools to more comprehensively study the impacts of adaptive learning in a flipped STEM course.

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AUTHORS

Autar Kaw

Autar Kaw is a professor of Mechanical Engineering at the University of South Florida. He is a recipient of the 2012 U.S. Professor of the Year Award (doctoral and research universities) from the Council for Advancement and Support of Education and the Carnegie Foundation for Advancement of Teaching. Professor Kaw's main scholarly interests are in engineering education research, adaptive, blended and flipped learning, open courseware development, and the state and future of higher education. Funded by National Science Foundation, under Professor Kaw's leadership, he and his colleagues from around the nation have developed, implemented, refined, and assessed online resources for an open courseware in Numerical Methods. This courseware annually receives 1,000,000+ page views, 2,000,000+ views of the YouTube lectures, and 90,000+ visitors to the "numerical methods guy" blog. He has written more than 100 refereed papers, and his opinion editorials have appeared in the Tampa Bay Times, Tampa Tribune, and Chronicle Vitae.

Renee Clark

Dr. Renee Clark serves as the Director of Assessment for the University of Pittsburgh's Swanson School of Engineering and its Engineering Education Research Center (EERC), where her research focuses on assessment and evaluation of engineering education research projects and initiatives. She received her Ph.D. in Industrial Engineering from the University of Pittsburgh. Dr. Clark has published articles in the Journal of Engineering Education, Advances in Engineering Education, and Risk Analysis.

Eleonora Delgado

Eleonora Delgado is a master's student in the Department of Mechanical Engineering at the University of South Florida. She graduated magna cum laude from the University of South Florida with a B.S. in Mechanical Engineering. Her areas of interest include education research, vibrations and machine design. She developed lessons on an adaptive learning platform for a course in Numerical Methods.

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Nicholas Abate

Nicholas Abate attended the University of South Florida where he obtained a Bachelor's degree in Mechanical Engineering, graduating Summa Cum Laude. During his time at USF, he was an active member of the Society of Aeronautics and Rocketry and the Society of Automotive Engineers. In his final year of academia, Nicholas worked with Professor Kaw as an undergraduate research and learning assistant for a numerical methods course to study the effectiveness of flipped classrooms with adaptive learning.

REFERENCES

1. Freeman S, Eddy SL, McDonough M, Smith M, Okoroafor N, Jordt H, Wenderoth M. Active learning increases student performance in science, engineering, and mathematics. Proceedings of the National Academy of Sciences. 2014;111(23): 8410-8415.

2. Flipped Learning. A community resource brought to you by the Flipped Learning Network http://flippedlearning.org. Accessed December 6, 2018.

3. Clark R, Kaw A, Lou Y, Scott A, Besterfield-Sacre M. Evaluating blended and flipped instruction in numerical methods at multiple engineering schools. *International Journal for the Scholarship of Teaching and Learning*. 2018;12(1): Article 11.

4. Crouch CH, Mazur E. Peer instruction: ten years of experience and results. *American Journal of Physics*. 2001;69(9):970-977.

5. Zhang P, Ding L, Mazur E. Peer instruction in introductory physics: a method to bring about positive changes in students' attitudes and beliefs. *Phys. Rev. Phys. Educ. Res.* 2017; 13(1).

6. Wieman CE. Large-scale comparison of science teaching methods sends clear message. Department of Physics and Graduate School of Education, Stanford University. 2014;111(23):8319-8320

7. Kothiyal A, Majumdar R, Murthy S, Iyer S. Think-pair-share in a large CS1 class: does learning really happen? Proceedings of the 2014 Conference on Innovation and Technology in Computer Science Education (pp. 51-56). Uppsala, Sweden.

8. Lyman F. Think-pair-share: an expanding teaching technique: MAA-CIE Cooperative News. *Creative Education.* 2017;8(1): 1-2.

9. Brown J. Personalizing Post-Secondary Education: An Overview of Adaptive Learning Solutions for Higher Education. Ithaka S&R. https://sr.ithaka.org/wp-content/uploads/2015/08/SR_Report_Personalizing_Post_Secondary_Education_31815_0.pdf. Accessed December 6, 2018.

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10. Tharayil S, Borrego M, Prince M, Nguyen K, Shekhar P, Finelli C, Waters C. Strategies to mitigate student resistance to active learning. *International Journal of STEM Education.* 2018;5(7):1-16.

11. King A. *Inquiry as a Tool in Critical Thinking*. San Francisco, CA: Jossey-Bass Publishers 1994.

12. Lage M, Platt G, Treglia M. Inverting the classroom: a gateway to creating an inclusive learning environment. *Journal of Economic Education*. 2000;31(1):30-43.

13. Kaw A, Hess M. Comparing effectiveness of instructional delivery modalities in an engineering course. *International Journal of Engineering Education*. 2007;23(3):508-516.

14. Bishop JL, Verleger MA. The flipped classroom: a survey of the research. Proceedings of 120th ASEE Annual Conference & Exposition. Atlanta, GA: ASEE. https://www.asee.org/public/conferences/20/papers/6219/download. Accessed December 6, 2018.

15. Barba L, Kaw A, LeDoux JM, Guest editorial: flipped classrooms in STEM. *ASEE Advances in Engineering Education*. 2016;5(3).

16. Chi M, Wylie R. The ICAP framework: linking cognitive engagement to active learning outcomes. *Educational Psychologist.* 2014;49(4):219-243.

17. Karabulut-Ilgu A, Cherrez JN, Jahren CT. A systematic review of research on the flipped learning method in engineering education. *British Journal of Educational Technology.* 2018;49(3): 398–411.

18. Woods DR. *Problem-Based Learning: How to Gain the Most from PBL*. Waterdown, ON: W L Griffen Printing; 1994.

19. Ambrose SA, Bridges MW, Dipietro M, Lovett MC, Norman MK. *How Learning Works: Seven Research-Based Principles for Smart Teaching.* 1st ed. San Francisco, CA: Jossey-Bass; 2010.

20. VanLehn K. The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*. 2011;46:4, 197-221

21. Cronbach LJ. The two disciplines of scientific psychology. *American Psychologist*. 1957;12(11): 671- 684.

22. Sleeman D, Brown JS. *Intelligent Tutoring Systems*. London, U.K.: Academic Press, 1982.

23. Bloom B. The 2 sigma problem: the search of group instruction as effective as one-to-one tutoring. *Educational Researcher*. 1984;13(6):4-16.

This article is protected by copyright. All rights reserved.

Author Manuscript

24. Brusilovsky P, Peylo C. Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education*. 2003;13:156-169.

25. Knewton: Education for Everyone. http://Knewton.com. Accessed December 6, 2018.

26. Create Learning Experiences As Unique As Your Students. Address Individual Student Needs, Increase Engagement and Improve Student Outcomes. Smart Sparrow Website. http://smartsparrow.com. Accessed December 6, 2018.

27. We're transforming the way the world learns. Desire2Learn Website. https://www.d2l.com/. Accessed December 6, 2018.

28. Yarnall L, Means B, Wetzel T. Lessons Learned From Early Implementations of Adaptive Courseware. https://www.sri.com/sites/default/files/publications/almap_final_report.pdf. Accessed December 6, 2018.

29. Quinton S. Georgia State Improved Its Graduation Rate by 22 Points in 10 Years. The Atlantic. http://www.theatlantic.com/education/archive/2013/09/georgia-state-improved-itsgraduation- rate-by-22-points-in-10-years/279909/. Published September 23, 2013. Accessed December 6, 2018.

30. ASU and Math Readiness. http://www.knewton.com/asu/. Accessed December 6, 2018.

31. Dziuban CD, Moskal PD, Cassisi, J, Fawcett, A. Adaptive learning in

psychology: wayfinding in the digital age. *Online Learning*. 2016;20(3):74–96.

32. Alli N, Rajan R, Ratliff G. How Personalized Learning Unlocks Student Success. EDUCAUSE Review Website. https://er.educause.edu/~/media/files/articles/2016/3/erm1621.pdf. Accessed December 6, 2018.

33. Dziuban C, Howlin C, Moskal P, Johnson C, Parker L, Campbell M. Adaptive learning: a stabilizing influence across disciplines and universities. *Online Learning*. 2018;22(3):7-39.

34. Kaw A, Besterfield-Sacre M. Transforming a flipped STEM course through adaptive learning. https://www.nsf.gov/awardsearch/showAward?AWD_ID=1609637. Accessed December 6, 2018.

35. Clark, R and Kaw, A, Benefits of Adaptive Lessons for Pre-Class Preparation in a Flipped Numerical Methods Course, revised manuscript under review at *International Journal of Mathematical Education in Science and Technology*, 2018.

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Author Manuscript

36. Austin E, Gibson G, Deary I, McGregor M, Dent J. Individual response spread in self-report scales: personality correlations and consequences. *Personality and Individual Differences*. 1998;24(3):421–438.

37. Fan X, Miller B, Park K, Winward B, Christensen M, Grotevant H, Tai R. An exploratory study about inaccuracy and invalidity in adolescent self-report surveys. *Field Methods*. 2006;18(3):223–244.

38. Salaberry R. The use of technology for second language learning and teaching: a retrospective. *Modern Language Journal*. 2001;85(1):39–56.

39. Steif P, Dollár A. Study of usage patterns and learning gains in a web-based interactive static course. *Journal of Engineering Education.* 2013;98(4):321-333.

40. Norusis MJ. *SPSS 13.0 Guide to Data Analysis*. Upper Saddle River, NJ: Prentice Hall.

41. Krueger, R. *Focus Groups: A Practical Guide for Applied Research*. Thousand Oaks, CA: SAGE Publications, New York: 1994.

TABLE 1. Final Exam Comparison between Flipped Class With and Without Adaptive Learning.

	Flipped	Flipped with Adaptive	*p*-value	Effect size (*d*)
Average, $\bar{x}$	51.2	52.1	0.547	0.12
Standard deviation, *s*	14.8	14.9		
Number of Participants, *n*	88	146		

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TABLE 2: Correlations of Exam Score with Adaptive Platform Metrics for all Lessons

Fall 2017-Spring 2018	Correlation, *r*			
	Total Attempts	Total Hours Spent	Total Raw Score	Total Actual Score
Final Exam (Smart Sparrow topics only)	-0.173	-0.003	0.350	0.138
p-value	0.057	0.972	< 0.0005	0.131

TABLE 3: Lesson Completion Percentages

	Fall 2017	Spring 2018
Lesson	Percentage of Students Completing Assignment (%)	
Bisection Method	81.3	94.3
Newton Raphson Method	73.6	91.4
Definition of Matrices	95.6	97.1
Binary Operations on Matrices	91.2	92.9
Setting up Problems in Matrix Form	87.9	90.0
Inverse of a Square Matrix	90.1	91.4
Gaussian Elimination	82.4	85.7
LU Decomposition	72.5	91.4
Partial Derivative	95.6	97.1
Simple Statistics	91.2	95.7
Finding the Minimum of a Function	91.2	94.3
Linear Regression	80.2	91.4
Nonlinear Regression	79.1	85.7
Adequacy of Linear Regression Models	79.1	90.0
Trapezoidal Rule	89.0	90.0
Gauss Quadrature Rule	83.5	91.4
Discrete Data Integration	81.3	81.4
Minimum	72.5	81.4

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TABLE 4: Adaptive States Utilized

Pre-Req/New	Lesson	Fall 2017 States Used	Fall 2017 Max States	Fall 2017 %	Spring 2018 States Used	Spring 2018 Max States	Spring 2018 %
New	Bisection Method	31	48	64.6%	32	48	66.7%
New	Newton Raphson Method	41	92	44.6%	58	92	63.0%
Pre	Definition of Matrices	23	63	36.5%	17	63	27.0%
Pre	Binary Operations on Matrices	10	27	37.0%	9	27	33.3%
Pre	Setting up Problems in Matrix Form	34	46	73.9%	8	18	44.4%
Pre	Inverse of a Square Matrix	9	18	50.0%	35	46	76.1%
New	Gaussian Elimination	56	59	94.9%	54	59	91.5%
New	LU Decomposition	34	38	89.5%	34	38	89.5%
Pre	Partial Derivative	2	3	66.7%	11	12	91.7%
Pre	Simple Statistics	10	10	100.0%	10	10	100.0%
Pre	Finding the Minimum of a Function	11	12	91.7%	11	12	91.7%
New	Linear Regression	62	67	92.5%	54	67	80.6%
New	Nonlinear Regression	47	52	90.4%	43	52	82.7%
New	Adequacy of Linear Regression Models	36	59	61.0%	38	59	64.4%
New	Trapezoidal Rule	21	21	100.0%	21	21	100.0%
New	Gauss Quadrature Rule	52	62	83.9%	52	62	83.9%
New	Discrete Data Integration	43	53	81.1%	34	53	64.2%

Pre = pre-requisite lesson

TABLE 5: Completion Time before Deadline

Lesson	Fall 2017 Mean Hours Completed Before Deadline Without Outliers (hrs)	Fall 2017 *s*	Spring 2018 Mean Hours Completed Before Deadline Without Outliers (hrs)	Spring 2018 *s*
Bisection Method	57.9	*64.8*	38.2	*33.5*
Newton Raphson Method	51.9	*72.8*	34.7	*34.0*
Definition of Matrices	47.3	*25.9*	26.0	*22.8*
Binary Operations on Matrices	47.3	*34.5*	29.7	*26.2*
Setting up Problems in Matrix Form	40.6	*34.1*	26.2	*23.1*
Inverse of a Square Matrix	33.2	*29.5*	26.7	*23.6*
Gaussian Elimination	11.2	*9.7*	15.6	*15.3*
LU Decomposition	10.4	*4.5*	15.9	*17.6*
Partial Derivative	39.4	*35.0*	60.9	*32.9*
Simple Statistics	39.0	*34.3*	66.1	*39.5*
Finding the Minimum of a Function	38.1	*34.8*	50.7	*27.5*
Linear Regression	30.2	*27.3*	54.3	*35.6*
Nonlinear Regression	24.5	*25.0*	52.3	*40.2*
Adequacy of Linear Regression Models	12.5	*12.9*	25.3	*25.6*

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Trapezoidal Rule	14.1	*12.6*	23.4	*28.1*
Gauss Quadrature Rule	18.6	*18.7*	31.3	*33.0*
Discrete Data Integration	10.7	*8.9*	27.7	*34.7*
Minimum	10.4		15.6	

TABLE 6: Mean Hours Spent on a Lesson

	Fall 2017		Spring 2018	
Lesson	Mean Hours Spent Without Outliers (hrs)	*s*	Mean Hours Spent Without Outliers (hrs)	*s*
Bisection Method	0.6	*0.4*	0.6	*0.3*
Newton Raphson Method	0.6	*0.3*	0.7	*0.4*
Definition of Matrices	0.3	*0.2*	0.3	*0.3*
Binary Operations on Matrices	0.1	*0.1*	0.9	*6.2*
Setting up Problems in Matrix Form	0.2	*0.1*	0.2	*0.1*
Inverse of a Square Matrix	0.6	*0.4*	0.7	*0.9*
Gaussian Elimination	0.9	*0.5*	0.9	*0.5*
LU Decomposition	1.4	*0.8*	2.1	*4.5*
Partial Derivative	0.1	*0.0*	0.0	*0.0*
Simple Statistics	0.2	*0.1*	0.2	*0.6*
Finding the Minimum of a Function	0.3	*0.2*	0.3	*0.2*

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Linear Regression	1.2	*0.6*	1.2	*2.4*
Nonlinear Regression	1.2	*1.0*	1.0	*0.5*
Adequacy of Linear Regression Models	1.2	*1.1*	1.3	*1.7*
Trapezoidal Rule	1.3	*0.8*	1.4	*1.6*
Gauss Quadrature Rule	1.3	*1.1*	1.6	*2.9*
Discrete Data Integration	0.6	*0.5*	0.5	*0.2*

TABLE 7: Raw Lesson Score

	Fall 2017		Spring 2018	
Lesson	Mean Raw Score Without Outliers (%)	*s*	Mean Raw Score Without Outliers (%)	*s*
Bisection Method	57.6	*12.8*	51.5	*15.1*
Newton Raphson Method	35.3	*6.9*	32.7	*6.8*
Definition of Matrices	27.5	*2.9*	26.1	*2.7*
Binary Operations on Matrices	26.8	*1.0*	26.3	*1.4*
Setting up Problems in Matrix Form	44.4	*0.0*	44.1	*1.9*
Inverse of a Square Matrix	45.2	*13.4*	45.2	*13.1*
Gaussian Elimination	41.0	*14.7*	39.0	*12.5*

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LU Decomposition	46.8	*16.4*	46.7	*13.7*
Partial Derivative	33.0	*1.9*	33.2	*1.3*
Simple Statistics	48.9	*10.7*	47.3	*10.9*
Finding the Minimum of a Function	36.4	*7.0*	35.3	*8.0*
Linear Regression	38.8	*12.3*	40.2	*11.3*
Nonlinear Regression	45.0	*23.4*	42.0	*18.7*
Adequacy of Linear Regression Models	52.3	*21.6*	56.8	*19.7*
Trapezoidal Rule	25.5	*9.2*	24.7	*9.3*
Gauss Quadrature Rule	40.4	*14.0*	37.8	*12.5*
Discrete Data Integration	53.0	*21.8*	55.8	*19.1*

TABLE 8: Focus Group Questions

1. Did the Smart Sparrow adaptive platform impact your learning or understanding more so than other methods for studying, learning, or reviewing content? Why do you feel this was the case?
2. Discuss your satisfaction with the Smart Sparrow adaptive software and reasons for it.
3. Did the Smart Sparrow adaptive software impact your engagement with the course material?
4. Compare and contrast your learning of the topics covered by Smart Sparrow versus those not covered by Smart Sparrow.

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TABLE 9: Coding Scheme for Content Codes

Category Description	Code
Benefits Smart Sparrow videos assist with preparing for a lecture. Smart Sparrow assists with understanding or learning the material, including increasing the exposure. Smart Sparrow assists in driving accountability with the videos or material in general.	MATPREP
Quiz or questions included alongside lecture - able to confirm, reinforce, or gain understanding via the questions.	QUIZQUES
Smart Sparrow provides convenience, tailoring, simplicity, and/or multiple resources. Examples: All resources available from the same website. Can do according to one's own time, pace, or as many times as desired, including infinite retries and re-watching of videos. Smart Sparrow "walks you through."	CONVENIENT
Drawbacks/Suggestions Smart Sparrow did not indicate exactly what was done wrong, why it was wrong, nor provide the solution. Provide detailed solutions or guidance.	NOTCLEAR
High workload or time-consuming.	WOR
Access to lessons or questions limited. Questions not available again until video re-watched. Could not review lessons afterward. Smart Sparrow not accessible via phone. Video not available when working the problem (i.e., place on the same page as the problem).	ACCESS
Inaccurate feedback on student answers provided by SS. Smart Sparrow feedback not sensitive to small differences between provided and expected answers.	INACCFEED

TABLE 10: Focus Group Question 1: Student Counts

				% of Participants	
Group	Positive Response	Negative Response	Total Participants	% Positive Responses	% Negative Responses
Other-than-white-males	4	1	9	44%	11%
White males	3	4	11	27%	36%

TABLE 11: Focus Group Question 2: Student Counts

				% of Participants	
Group	Positive Response	Negative Response	Total Participants	% Positive Responses	% Negative Responses
Other-than-white-males	5	2	9	56%	22%
White males	1	5	11	9%	45%

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TABLE 12: Focus Group Question 3: Student Counts

				% of Participants	
Group	Positive Response	Negative Response	Total Participants	% Positive Responses	% Negative Responses
Other-than-white-males	5	1	9	56%	11%
White males	6	3	11	55%	27%

TABLE 13: Focus Group Question 4: Student Counts

					% of Participants		
Group	Learning of Smart Sparrow topics better	Learning of Smart Sparrow topics *not* better	No difference	Total Participants	% Learning of Smart Sparrow topics better	% Learning of Smart Sparrow topics *not* better	% No difference
Other-than-white-males	6	1		9	67%	11%	
White males	4		4	11	36%		36%

Figures

Figure 1: A typical flowchart for an adaptive lesson.

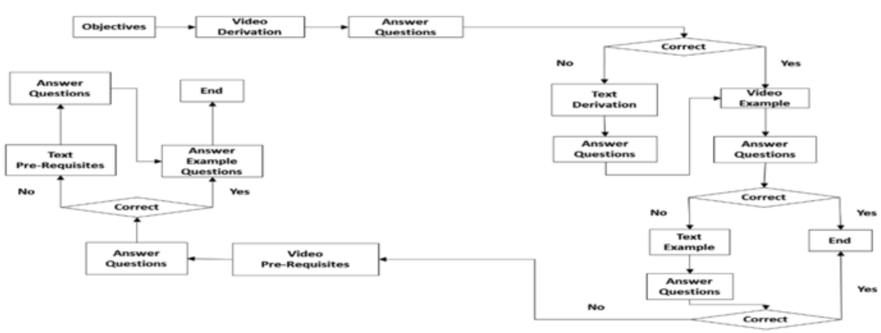

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Figure 2: Typical content of an adaptive lesson

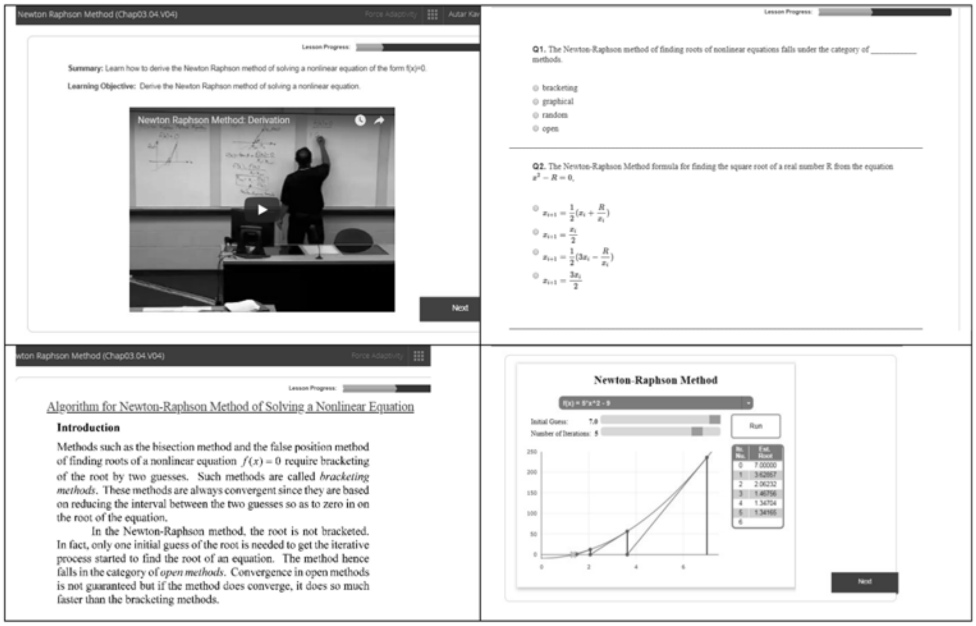

Figure 3: Histogram of hours before deadline a lesson is completed for a typical lesson.

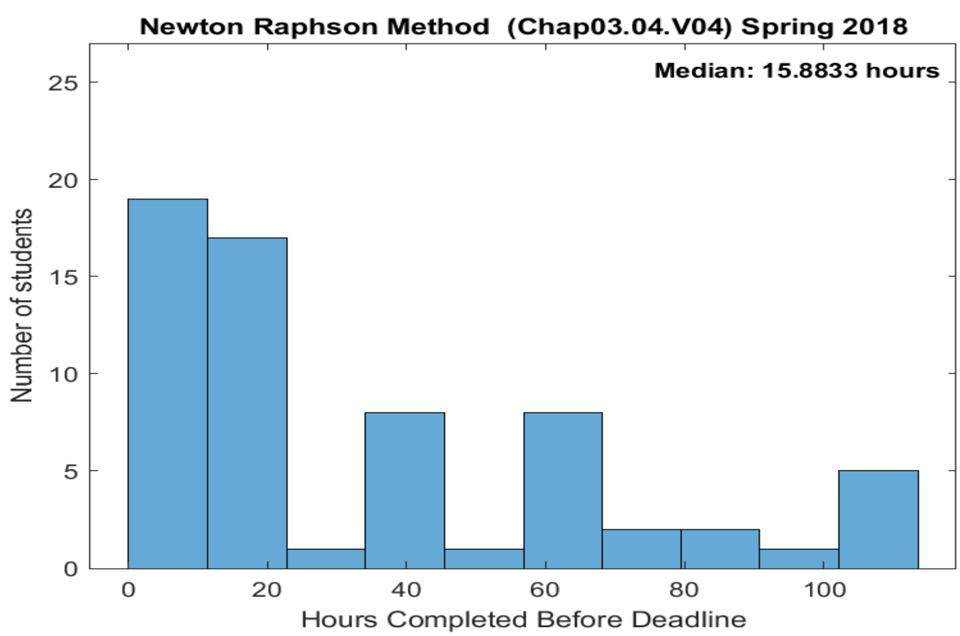

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Figure 4: Histogram of typical amount of time spent on a lesson

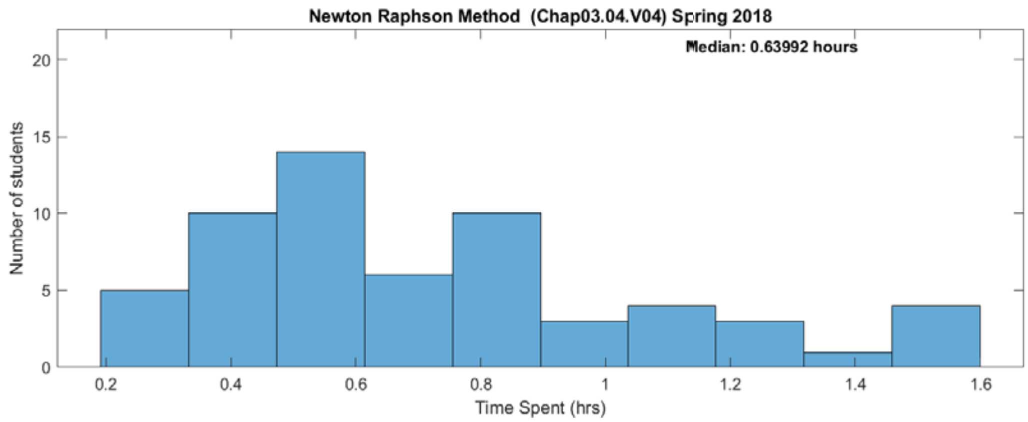
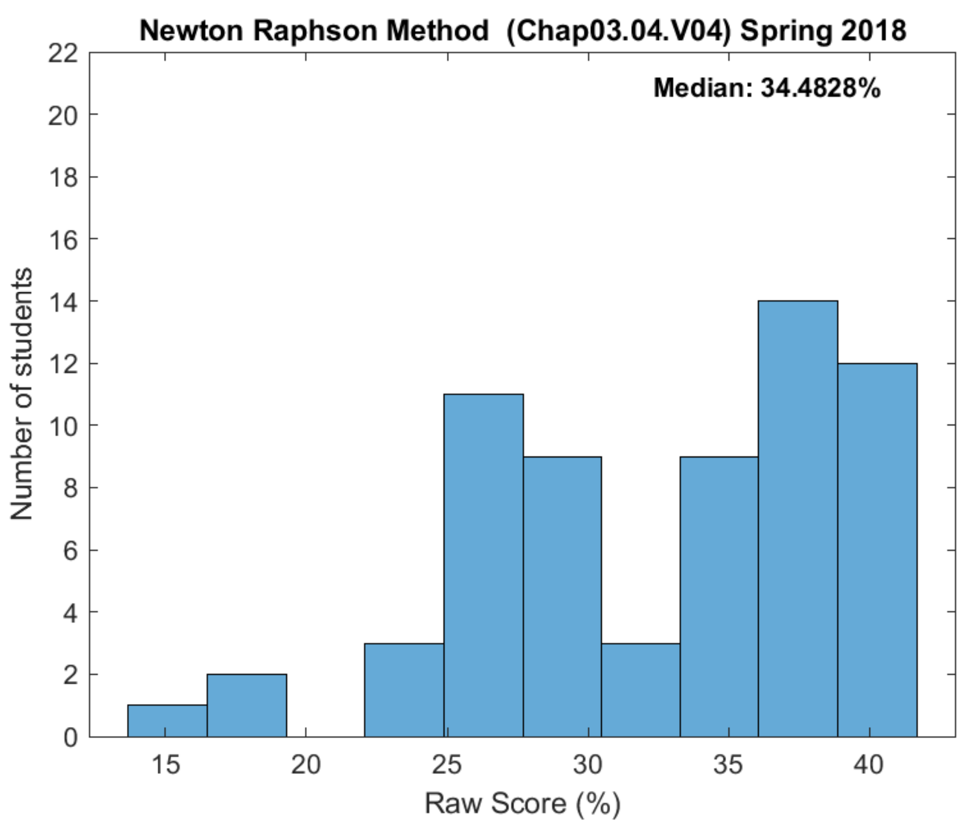


Figure 5: Histogram of raw score of for a typical lesson.



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