ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE
Paper ID #36538

Development, Implementation, Refining and Revising of Adaptive Platform Lessons for an Engineering Course

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1. Introduction

Since the high-profile meta-analyses (Freeman et al., 2014, Theobald et al., 2020) of undergraduate STEM courses, active learning has become a standard in higher education pedagogy. One way to provide active learning is through flipped learning - "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 dynamic, interactive learning environment where the educator guides students as they apply concepts and engage creatively in the subject matter" (Talbert, 2017, Flip Learning, 2019).

A typical flipped classroom involves pre-class, in-class, and post-class learning. The pre-class learning is done individually by the student and generally includes some combination of video lectures, textbook content, and online assessment but falls under the one-size-fits-all (i.e., non-personalized) approach. The pre-class learning gets the student ready for the in-class segment, which involves well-thought-out conceptual and procedural exercises to improve the level of learning of students and mini-lectures to clarify student misconceptions and difficulties with the learning materials. The in-class segment is followed by post-class learning, which includes completing the topic, solving problem sets from the textbook, and projects to improve students' higher-level thinking skills.

Flipped classes have been found to be relatively successful when compared to the traditional lecture modality. Recent meta-analyses (Talbert, 2018, Lag and Sale, 2019) based on research articles in eight electronic reference databases show an average effect size[1] of d=0.24 for cognitive learning in favor of flipped classes over traditional ones. The average effect size on student satisfaction was lower at d=0.16. A metastudy of 63 papers for K-12 students from 2021 by Shao and Liu shows an average effect size of d=0.63, finding better results for classes smaller than 120 students and humanities courses. Also, a meta-study by Birgili et al. (2021) shows similar increases in student performance and affective outcomes of engineering students.

Flipped classrooms do indeed have some challenges, though. One significant challenge is finding suitable pre-class learning activities to improve student preparation and the subsequent classroom environment, including student engagement (Shekhar et al., 2019, Finelli et al., 2018, Tharayil et al., 2018). Many students come unprepared to the classroom and adversely affect the group experience. These challenges were experienced by the authors of this paper, who teach a course in Numerical Methods. To address this challenge of under-preparation with pre-class learning materials, we developed adaptive learning lessons to remedy the one-size-fits-all approach to pre-class learning.

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[1] Effect size is the difference between an experimental and a control group and is measured as (Mean of the experimental group–Mean of the control group)/(Standard Deviation). Rules of thumb for effect sizes being small or large should be based on comparable studies in the field. An average effect size for education interventions that are published in the literature is d=0.38 (Hattie, 2008).

Adaptive lessons delivered via online platforms provide personalized and flexible learning by monitoring student progress and performance. Using learning algorithms, the platform subsequently provides an individualized learning path and motivates students optimally. Adaptive lesson platforms (ALPs) have shown their power on a large scale in undergraduate STEM education. For example, using ALPs, Georgia State University reduced the DFW (D and F grades and withdrawals) rate in college algebra from 43% to 21% (Quinton, 2013) in a sample of 7,500 students and in developmental mathematics courses (ACT, 2019, Knewton, 2019), ASU reduced the DFW rate from 16% to 7% in a sample of 2,000 students.

The use of adaptive lessons in engineering flipped classrooms is limited, though. Kakosimos (2015) used adaptive learning in a flipped course in a Chemical Engineering Fluid Operations course. However, the control group was from a different course, so a direct comparison of the effectiveness was not possible. The first and last author of this paper conducted an exploratory study of the use of adaptive learning in the flipped classroom in the Numerical Methods course. In a final examination, a positive effect size of d=0.12 for all students was found for flipped-with-adaptive classrooms over the flipped-without-adaptive classroom (Kaw et al., 2019). In addition, in a classroom environment inventory, there were positive effects for flipped-with-adaptive over flipped-without-adaptive-learning for all environment dimensions. Araujo et al. (2019) found that adaptive lessons in a flipped class improved test scores but without statistically significant results.

Given the limited research conducted on the use of adaptive learning in flipped classrooms and the success shown in the exploratory study (Clark and Kaw, 2020) by the authors of this paper, a fuller and more diverse investigation of the effectiveness of adaptive learning for pre-class learning in flipped classrooms is being conducted by measuring changes in cognitive and affective impacts on the student.

But, before the study could start, well-thought-out adaptive lessons had to be constructed. This paper discusses the development, implementation, refining, and revising of the ALP lessons for pre-class learning in a Numerical Methods flipped course and examines the nature of the student data that the ALP collects.

2. Development of Adaptive Lessons

Three instructors from three universities began the work of developing the ALP lessons for a course in Numerical Methods in Fall 2020 under an NSF-funded grant (Kaw et al., 2020). The universities included a large southeastern public university, an HBCU from a small southeastern state, and a large southwestern urban university, where the courses are taught to Mechanical, Electrical, and Civil Engineering majors, respectively. The work was monitored by an external evaluator in the beginning so that we would have an unbiased assessment of the process. The first item was to enumerate the various *topics* and break each one into individual *objectives*.

The eight topics of the course were the following.

1) Introduction to Scientific Computing
2) Numerical differentiation

3) Nonlinear Equations
4) Simultaneous Linear Equations
5) Interpolation
6) Regression
7) Numerical Integration
8) Numerical Solution of ODEs

Each of the topics was broken down into chapters and are called “objectives.” by the ALP platform. There are a total of 30 objectives in the course. For example, for the topic of “Numerical Differentiation”, there are three “objectives” as follows:

1) Prerequisites to Numerical Differentiation
2) Numerical Differentiation of Continuous Functions
3) Numerical Functions Given at Discrete Points.

Each of the objectives was then divided into individual lessons called *nodes*. There are a total of 121 nodes for the course. For example, we have three nodes for the “Numerical Differentiation of Continuous Functions” objective.

1) Numerical Differentiation of Continuous Functions - First Derivative
2) Numerical Differentiation of Continuous Functions – Second Derivative
3) Error Analysis of Divided Difference Formulas

In a prior pilot study at a large public southeastern university, the first author had developed ALP lessons for the pre-class learning for four (Nonlinear Equations, Simultaneous Linear Equations, Regression, Integration) of the eight topics covered in a Numerical Methods course. The lessons learned from the pilot study informed the process.

The three instructors met twice per month to discuss the content that would form each node. The main discussion of the meetings centered on what a student would be expected to learn before coming to class, choosing appropriate content, agreeing on prerequisite nodes, and choosing and formulating new assessment questions. Lessons were then created by the first author and his student team using a commercially available platform, RealizeIT (RealizeIT, 2021). The content was tested by learning assistants and instructors. It is important to note that a significant percentage of the content, such as videos and textbook material, was available through previously funded work (Kaw et al., 2011, Kaw and Garapati, 2012, Owens, Kaw, Hess, 2012). The new adaptive lessons and the revised existing ones were completed in December 2020.

Each node of the ALP lessons includes five sections (overview, learning objectives, video lectures, textbook content, and assessment), as shown in Figure 1.

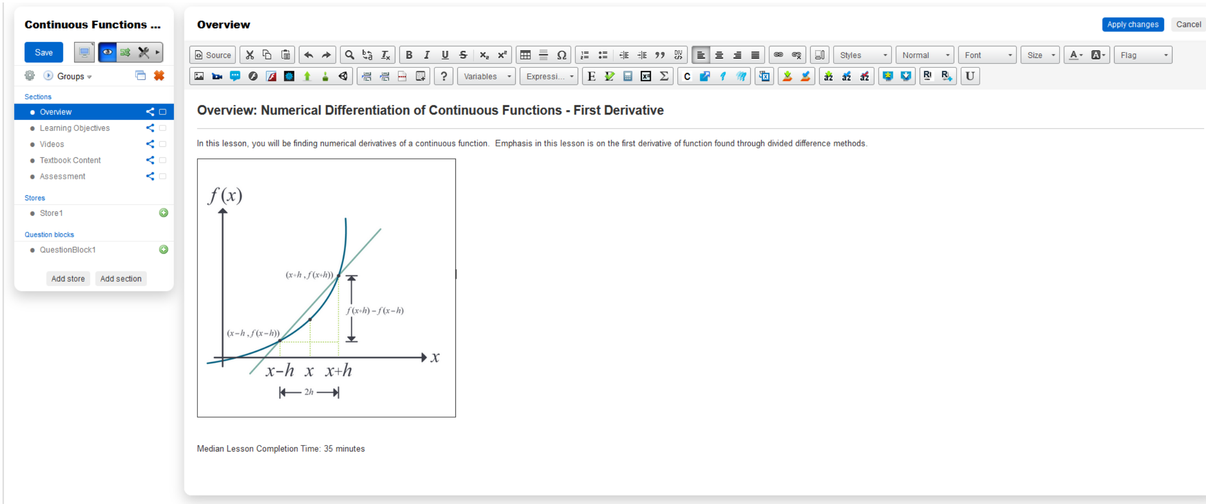


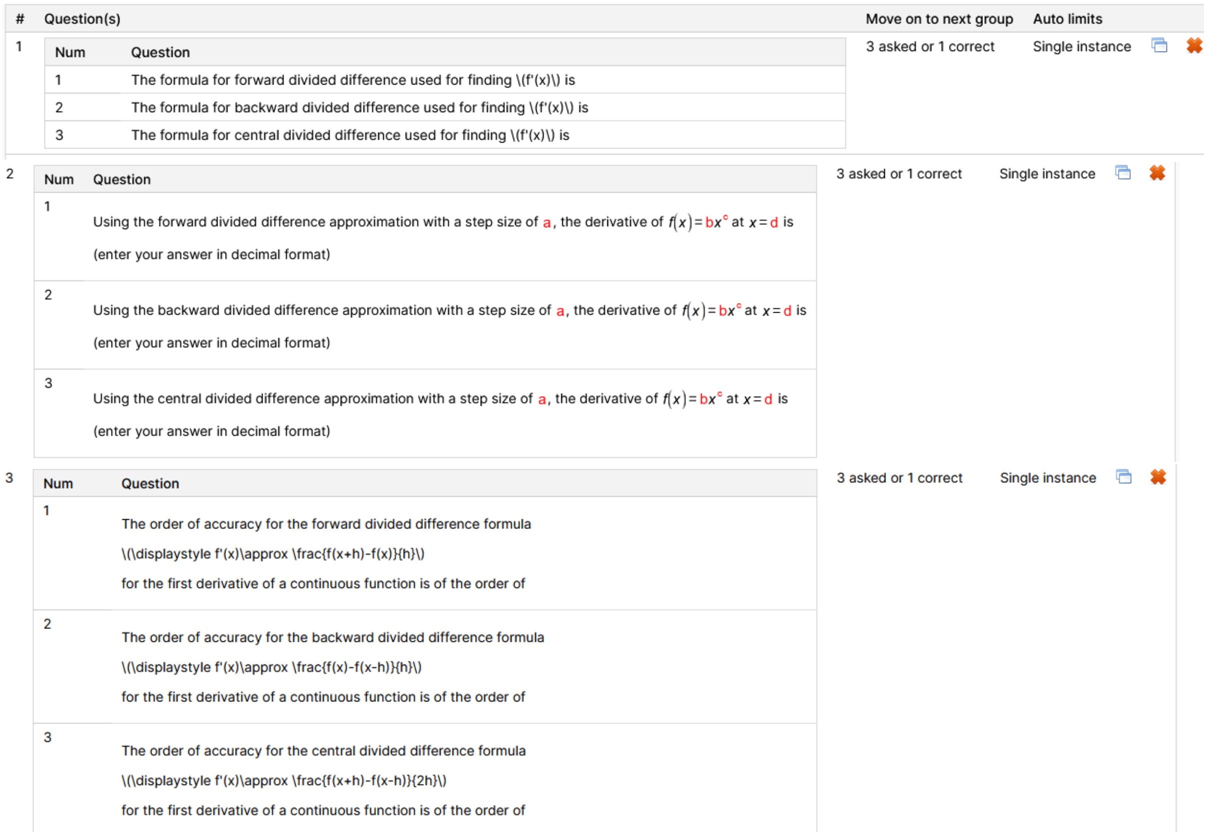
Figure 1. The five sections of a typical node

The introduction section includes a short overview of the topic, while the learning objectives section delineates what the student should know by the end of the node.

The video section consists of relevant lectures. For example, for the "Numerical Differentiation of Continuous Functions – First Derivative" node, the student is presented with three video lectures describing the three numerical differentiation methods: the forward–divided–difference method, backward-divided-difference method, and central-divided-difference method. These three videos had a total length of 33 minutes.

The textbook content section includes relevant sections from the textbook. The section is provided as an alternative to the lecture videos or as an additional resource.

The last section of an ALP lesson is the assessment. For this node, the question grouping for the assessment is given in Figure 2. One question is presented randomly to the student from each of the three question blocks. Two blocks have multiple-choice questions worth 1 point each, and one block has algorithmic questions worth 3 points each. To move to a node for which the attempted node is a prerequisite, a student must receive a minimum score of 59% for the current node. The score is based on interaction with the node, successful attempts of the questions asked, level of prerequisite knowledge, and propriety features of the RealizeIT ALP algorithm. A student can go through the lesson as many times as they like, but highly unsuccessful attempts reduce the score to discourage guessing.



#	Question(s)		Move on to next group	Auto limits
1	Num	Question	3 asked or 1 correct	Single instance
	1	The formula for forward divided difference used for finding \(f'(x)\) is		
	2	The formula for backward divided difference used for finding \(f'(x)\) is		
	3	The formula for central divided difference used for finding \(f'(x)\) is		
2	Num	Question	3 asked or 1 correct	Single instance
	1	Using the forward divided difference approximation with a step size of a, the derivative of $f(x)=bx^c$ at $x=d$ is (enter your answer in decimal format)		
	2	Using the backward divided difference approximation with a step size of a, the derivative of $f(x)=bx^c$ at $x=d$ is (enter your answer in decimal format)		
	3	Using the central divided difference approximation with a step size of a, the derivative of $f(x)=bx^c$ at $x=d$ is (enter your answer in decimal format)		
3	Num	Question	3 asked or 1 correct	Single instance
	1	The order of accuracy for the forward divided difference formula \(\displaystyle f'(x)\approx \frac{f(x+h)-f(x)}{h}\) for the first derivative of a continuous function is of the order of		
	2	The order of accuracy for the backward divided difference formula \(\displaystyle f'(x)\approx \frac{f(x)-f(x-h)}{h}\) for the first derivative of a continuous function is of the order of		
	3	The order of accuracy for the central divided difference formula \(\displaystyle f'(x)\approx \frac{f(x+h)-f(x-h)}{2h}\) for the first derivative of a continuous function is of the order of		

Figure 2. Question blocks for a typical node

3. Implementation of ALP Lessons

The adaptive lessons were tested for implementation in Spring 2021 at the first author's university. They counted for 15% of the students' final course grades. Each of the 30 objectives was presented as an assignment to students via the CANVAS learning management system. Each objective was released on a Thursday afternoon at the end of the classes for the week and due on a Tuesday afternoon 11 days later before the beginning of the classes for that week. The in-class activity was based on the work done by the deadline. Scores obtained on the objective were transferred automatically by the ALP to the CANVAS LMS an hour after the deadline. The ALP lessons remained accessible until the end of the semester for all students. The ALP lessons follow the W3C accessibility standards (W3C, 2022), while the university aids individual students through their Student Ability Services department. Accessibility standards followed in the ALP lessons include transcripts for videos, alternative textbook content to replace videos, use of LaTeX for readability of equations, and alternative text for figures.

4. Revising and Refining of ALP Lessons

Questions asked by students during office hours with the instructor and the TA, on the CANVAS LMS discussion board, and via emails were used to update the content of the ALP lessons, clarify questions, and revise hints offered by the platform. Also, comments from the end-of-semester surveys conducted by an independent assessment analyst were used to revise the adaptive lessons. For example,

1) All videos in the ALP lessons were updated to HD quality from 240p format.
2) The textbook content format was changed from an embedded PDF file to HTML to improve quality and meet web accessibility standards.

5. Case Study of Student Interactions with a Node

In this section, we ask the research question – How do students who made an A, B, and C grade in the course differ in their behavior in approaching the ALP lessons. Rather than looking at the group statistics of students who made an A, B, and C grade in the course, at this stage of the study, we look at how a typical student from each group interacted with the "Numerical Differentiation of Continuous Functions - First Derivative" node. Also, how to use the data to improve student success is beyond the scope of this paper as we are currently studying it in Spring 2022.

The node was made available on January 15, 2021, and was due to be completed by January 26, 2021, for credit towards the final course grade. A graded test that included this node was administered on February 5, 2021. The node remained available to students for review until the end of the Spring 2021 semester on May 8, 2021. Our best estimate regarding how long a student should/would spend on this node is as follows: Introduction 2 mins, Objectives 4 mins, Videos 33 minutes, Alternative Text if used instead of videos 20 mins, Alternative Text if used with videos 10 mins, and Questions 20 minutes. These amount to a total time of 45-60 mins to complete the node.

Two types of data were collected related to individual student engagement with nodes, namely 1) participation data and at the more aggregate level, 2) activity data. Participation data shows the duration of students' engagement with the content within a node, such as the introduction, learning material, and questions. An activity constitutes one or more participations within the node and may be viewed as a "sitting" or "attempt" at completing the contents and/or requirements of a node by an individual student. The ALP collects time data associated with participation, which is then summed to determine activity time. In addition, each activity is evaluated using a feature called "normresult" which is the platform's evaluation of the student's performance for the node. The normresult score is scaled to a value between 0 and 1. A normresult of -1 indicates an abandoned activity or an activity for which there were no assessment questions, and hence no performance evaluation was possible. It does not negatively affect the students' scores.

For the "Numerical Differentiation of Continuous Functions – First Derivative" node, the ALP recorded 237 distinct activities during the 2021 Spring semester for the 101 students enrolled in the course. Figure 3 shows a Box-Whisker plot of the activity durations.

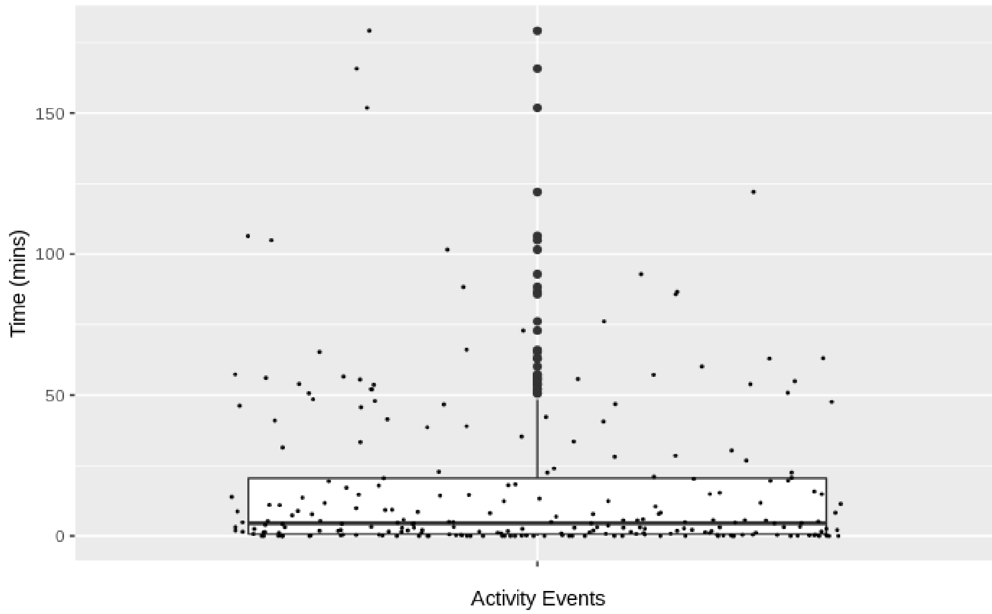


Figure 3. Distribution of activity times for the node

It is important to note that the activity times reported need to be carefully interpreted. Many of these said activities do not represent meaningful interactions between the student and the content. For example, students repeating the content in a node may quickly skip over the introduction and objectives sections and spend time on text, videos and/or questions. Disproportionately long activity times may also be recorded if a student abandons the node but does not close the browser window.

The activity time for this node is broken down by the day before the due date and is shown in Figure 4. Considering the due date of January 26, 2021, these results align with the expectation that most students access and complete the content immediately before the due date.

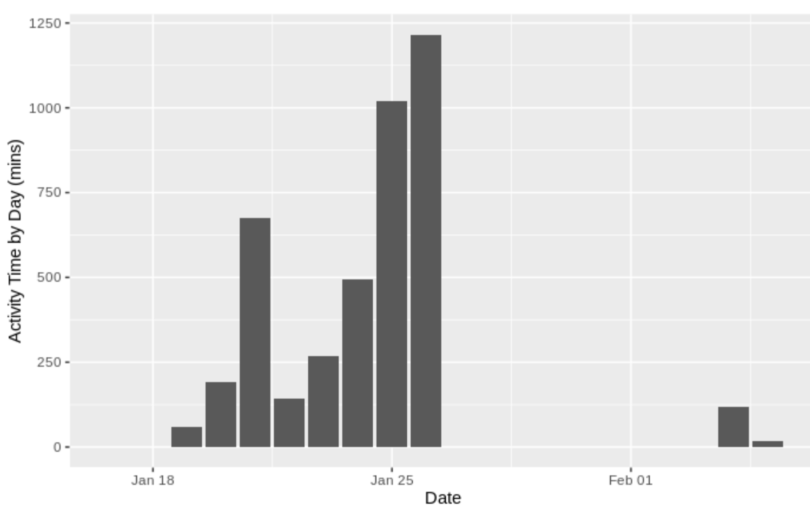


Figure 4. Activity time by date for the node.

Among the 101 students, we will focus on the activity and participation data of three students we refer to as A, B, C. The letters A, B, and C also correspond to the overall course grade they received at the end of the semester. The data collected by the ALP related to the activities of these students for this node are shown in Table 1. We have removed the fields unrelated to student activity, such as foreign keys and identifying fields, and kept only the fields directly related to the activity itself. Similarly, the participation data for these students is shown in Table 2.

Student A has one activity recorded for this node which has a duration of 47 minutes and a NormScore of 1. This record means the student completed the requirements of this node in one attempt with the maximum possible score. Within this activity, the student spent most of their time (40 minutes or 2324 seconds) on Learning Material and 7 minutes (380 seconds) on correctly answering the three required questions in the first attempt.

Table 1. Student activity data collected in the ALP

Record Id	**Student Name**	**Activity Date and Time**	**Time (mins)**	**NormResult**
21741	A	2021-01-21 21:48:53	46.7	1.0
22167	B	2021-01-25 13:52:59	41.0	0.6
22174	B	2021-01-25 14:34:05	2.0	1.0
22323	C	2021-01-25 18:35:00	2.7	-1.0
22324	C	2021-01-25 18:37:42	13.9	-1.0
22338	C	2021-01-25 18:52:13	5.6	-1.0
22340	C	2021-01-25 18:58:02	4.32	1.0

Table 2. Student participation data collected in the ALP.

Student Name	**Activity Record Id**	**Start Date and Time**	**Time (sec)**	**Nature Label**
A	21741	2021-01-21 21:48:53	81	Introduction
A	21741	2021-01-21 21:50:14	3	Introduction
A	21741	2021-01-21 21:50:17	2329	Learning material
A	21741	2021-01-21 22:29:06	5	Learning material
A	21741	2021-01-21 22:29:12	380	Questions
B	22167	2021-01-25 13:53:00	2092	Introduction
B	22167	2021-01-25 14:27:52	2	Introduction
B	22167	2021-01-25 14:27:54	4	Learning material
B	22167	2021-01-25 14:27:58	359	Questions
B	22174	2021-01-25 14:34:08	1	Introduction
B	22174	2021-01-25 14:34:09	1	Introduction
B	22174	2021-01-25 14:34:09	2	Learning material
B	22174	2021-01-25 14:34:11	115	Questions

C	22323	2021-01-25 18:35:00	1	Introduction
C	22323	2021-01-25 18:35:02	1	Introduction
C	22323	2021-01-25 18:35:02	2	Learning material
C	22323	2021-01-25 18:35:05	154	Questions
C	22324	2021-01-25 18:37:42	390	Introduction
C	22324	2021-01-25 18:44:12	1	Introduction
C	22324	2021-01-25 18:44:13	3	Learning material
C	22324	2021-01-25 18:44:17	16	Learning material
C	22324	2021-01-25 18:44:32	420	Questions
C	22338	2021-01-25 18:52:14	2	Introduction
C	22338	2021-01-25 18:52:15	0	Introduction
C	22338	2021-01-25 18:52:16	3	Learning material
C	22338	2021-01-25 18:52:19	1	Learning material
C	22338	2021-01-25 18:52:20	329	Questions
C	22340	2021-01-25 18:58:02	2	Introduction
C	22340	2021-01-25 18:58:04	1	Introduction
C	22340	2021-01-25 18:58:05	2	Learning material
C	22340	2021-01-25 18:58:07	253	Questions

Student B has two activities reported for the node. The first activity was 41 minutes long and was completed with limited success (NormScore of 0.6) in answering the questions in the node, where the student spent 6 minutes (359 seconds). Of particular interest here is the time spent in the Introduction part of the node, which is around 35 minutes (2092 seconds), but the content in that part of the node should only take a few minutes. In contrast, the student spent only 4 seconds on the Learning Materials in the node. The second activity starts immediately after the first one, and the student spent 2 minutes (115 seconds) on the assessment questions in the node and completed the node's requirements noted by the NormScore=1.

Student C has four consecutive activities that are relatively short, namely, 3, 14, 6, and 4 minutes. The student did not spend much time in the Learning Materials in any of the activities, and most of their time was spent on questions. After three unsuccessful attempts, the 4th attempt completed the node requirements.

The exact nature of what the students are doing while interacting with the nodes is not captured in the ALP. However, looking at the duration and in what parts of the node students are spending time, we see a distinct difference between these students as follows:

1. Student A spent much more time on the Learning Material than Students B and C.
2. Student A was very deliberate in answering the questions correctly and achieved this in the first attempt.
3. Student C had significantly more abandoned activities or unsuccessful attempts at answering assessment questions.
4. Student C seemed to be utilizing a "trial and error" approach to get the correct answers for the questions instead of spending time exploring the Learning Material content.

These distinctions show that it may be better for a student to spend reasonable time on the learning material such as lecture videos and textbook content before jumping to answer the assessment questions. These observations are being used to inform struggling students about how they should interact with ALPs.

Summary

One way to provide active learning is through the flipped classroom. However, finding suitable pre-class learning activities to improve student preparation and the subsequent classroom environment, including student engagement, can challenge the flipped modality. To address this challenge, adaptive learning lessons were developed for pre-class learning for a course in Numerical Methods. The lessons were then used as part of a research study to determine their cognitive and affective impacts. Thoughtful design and implementation of the adaptive lessons were completed prior to beginning the study. This paper discusses the development, implementation, refining, and revising of the adaptive learning platform (ALP) lessons for pre-class learning in a Numerical Methods flipped course. The paper also walks through the content of a typical lesson and shows the type of behavioral data collected by the adaptive learning platform by illustrating the interactions of three students of differing performance levels with a single lesson. In conjunction with the student's course grade, these interactions will be used in Fall 2022 to provide advice to struggling students about effective behaviors.

The first author and two other instructors who teach Numerical Methods collaborated on developing the adaptive lessons for the whole course. The work began in Fall 2020 by enumerating the various chapters and breaking each one into 30 individual objectives (assignments), which were then divided into individual nodes (lessons). Each lesson includes five sections (introduction, learning objectives, video lectures, textbook content, assessment). The three instructors met twice a month to discuss the content that provides the basis for each of the lessons. The main discussion of the meetings centered on what a student would be expected to learn before coming to class, choosing appropriate content, agreeing on prerequisites, and choosing and making new assessment questions. Lessons were then created using a commercially available platform called RealizeIT. The content was tested by learning assistants and instructors. The adaptive lessons were completed in December 2020.

The adaptive lessons were tested for implementation in Spring 2021 at the first author's university. Questions asked by students during office hours, on the LMS discussion board, and via emails while doing the lessons were used to update ALP content, clarify questions, and revise hints offered by the platform.

The paper discusses the process of development, implementation, revision, and refinement of adaptive learning platform lessons for pre-class learning for a numerical methods course that is taught in the flipped modality. Three test cases are discussed to show how students interact with a typical ALP lesson.

Acknowledgments

This material is based upon work supported partially by the National Science Foundation under Grant Number 2013271 and the Research for Undergraduates Program in the College of Engineering at the University of South Florida (USF). The authors would like to thank Colm Howlin, Sean O'Shea, and John Healy of RealizeIT for their help during the development and implementation of the adaptive lessons. We also thank Dr. Sarah Zappe of Zappe and Cutler Educational Consulting for her feedback on the manuscript. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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