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An Adaptive Learning Engineering Mechanics Curricular Sequence

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Abstract

Adaptive learning (AL) is a personalized learning approach that dynamically adjusts content, assessment, and feedback based on algorithms that monitor student progress, pace, or performance. The engineering mechanics introductory sequence (Physics I, Statics, Dynamics) is a gateway sequence that requires strong foundational knowledge, but students present with variable prerequisite knowledge and skills. Our goal was to develop AL materials that can elucidate conceptual connections across a sequence and provide just-in-time support for prerequisite remediation to enable individualized support that can be challenging to provide in large introductory courses.

We created AL courseware for Physics I, Statics, Dynamics, and prerequisite math concepts, implemented in Realizeit, an adaptive learning platform. AL courseware included learning content, quizzes, and algorithmic multi-part capstone homework problems that allowed each student to receive different numerical scenarios; overall, 190 lessons and 1900 interactive problems were implemented. We deployed these materials in Spring 2021 to 1224 students at North Carolina State University in the 3 sequence courses. Evaluation of the sequence development experience was achieved through pre- and post-course surveys delivered to the 3 faculty leads. Faculty surveys addressed perceptions of and interactions with the courseware during development and deployment. Detailed evaluation of student perceptions and platform usage was performed for the Dynamics course (130 students) using student pre/post surveys and AL analytics; in Dynamics, weekly AL modules were required for a grade, and students had access to AL prerequisite materials as part of the sequence design. The student survey addressed comfort with engineering and AL technology, and perceptions of the content and platform.

Evaluation revealed overall positive student perceptions in Dynamics. Student comfort with engineering improved from 81.1% to 87.5% pre- to post-course. Post-course perceptions revealed that satisfaction with the technology was expressed by 70.8% of students, and 83.3% found it helped them master skills. Importantly, relevant to implementation within a course sequence, 75.0% found it helped make connections between prior and new knowledge, and 79.2% found it somewhat, very or extremely helpful to transition into the dynamics class. Analytics revealed that students spent a substantial 2946.7 hours in the AL platform and completed 39,000 total questions (22.7 hours and 300 questions per student on average). In Dynamics, scores on the learning activities in Realizeit were significant predictors of a student's project and exam grades ($p<0.0001$). Notably, 48% and 20% of the variability in project and exam grades, respectively, were explained by the Realizeit score. This was a marked improvement over the relationship of homeworks and quizzes to exams and projects in an earlier semester without AL elements. Student feedback exposed the need for more examples and practice questions. Faculty reported students were more aware of concepts requiring support and asked more pertinent questions. In addition, faculty perceptions were more positive when AL materials were graded elements that substantially replaced non-AL course material compared to when they were used to supplement existing course materials. These results suggest that AL can enhance connections in the introductory mechanics sequence, but emphasize that adaptive content and assessments must be carefully integrated in course design and reveal the need for a large scope of practice questions to enhance student learning.

Introduction

Adaptive learning (AL) is a personalized learning approach that dynamically adjusts content, assessment, and feedback based on algorithms that monitor student progress, pace, or performance. Learning analytics from AL systems enable instructors to adapt instruction based on student needs and can identify at-risk students to provide interventions [1], [2]. AL courseware provides students increased control and engagement, real-time feedback to develop confidence and improve grades, while increasing degree completion [3]–[5]. Notably, there is strong potential that AL can disproportionately benefit underserved students. Active learning has resulted in significant reductions in achievement gaps in exam scores (33%) and passing rate (45%) for underrepresented minority (URM) students relative to non-URM [6]. Students who self-identify as racially minoritized, Pell-eligible, and first-generation have also reported an increased benefit from AL in their final course grade [7].

AL course redesigns have typically focused on STEM gateway courses with large enrollment, attrition, and failure rates (30-60%) that create obstacles to retention and time-to-degree [8]. The engineering mechanics introductory sequence (Physics I, Statics, Dynamics) is one such gateway sequence that requires strong foundational knowledge [9], but students often have variable prerequisite knowledge and skills [10]. Fostering a lasting understanding and retention of foundational concepts remains a challenge for faculty and students [11]. Although personalized learning is a key pathway to providing the necessary support for prerequisite remediation, it is challenging to achieve high-quality personalization in large classes. The affordances of modern AL technologies make it feasible to bring personalized learning pedagogy to scale and to automate remedial instruction or refreshers to directly support students entering this sequence who have variable high school mathematics and physics foundations [10], [12], [13]. Indeed, implementations of adaptive approaches in engineering have shown promise. For example, work by Prusty, et al. reported that adaptive tutorials for engineering mechanics resulted in reduced failure rates (from over 30% to 7% in 6 months), an increase in student satisfaction, positive student perceptions among first and second year mechanics students who overcame common threshold concepts (e.g., Newton's Laws of Motion), and increased conceptual understanding and engagement with the content [14], [15].

A particular challenge with AL implementation and adoption is the large amount of content that must be produced, particularly if remedial or prerequisite support is to be provided. While a new faculty user of AL may be able to implement the materials in their own course into an AL platform, it is a big effort to also implement the prerequisite concepts in math, science, or prior engineering classes necessary to support students. We propose that developing a "spine" of interconnected AL modules and courses can address this challenge through simultaneous development of multiple courses, allowing for interconnections between courses to be strengthened, and later courses to leverage the AL materials from earlier courses as refresher and support materials. Our goal was to develop AL materials for the introductory mechanics sequence that could elucidate conceptual connections across courses and provide just-in-time individualized support for prerequisite remediation that can often be challenging to provide in large introductory courses.

Methods

Development: We created adaptive courseware for Physics I, Statics, Dynamics, and prerequisite math concepts, and implemented the materials in Realizeit (Palatine, IL), an adaptive learning platform. We refer to the interconnected sequence of courses as an AL spine. Our implementation team consisted of 3 faculty leads at North Carolina State University, instructional design and evaluation support from the university instructional technology and design group (DELTA), implementation support and product design support from Realizeit, and graduate student support for quality testing. All lead faculty had developed materials for and taught one of the sequence courses more than 5 times previously. This team was part of a larger project supported by the UNC System (state university system) that also included affiliate faculty at 3 other universities in the UNC System (UNC-Charlotte, North Carolina A&T, East Carolina University) who contributed material to be included in the platform and tested the developed platforms in their own courses. For the current paper, we focus on the experience of the lead faculty and students at North Carolina State University.

Each of the faculty leads had already developed online learning materials covering math prerequisites, Statics, and Dynamics, which served as a foundation for the AL content, along with existing course maps, syllabi, and other course assets. To convert the materials for use in the AL spine, the faculty leads first evaluated course learning outcomes and content and created connectivity maps to identify prerequisite and repeated concepts. This allowed us to increase alignment and conceptual connectivity between and within courses; these links were directly represented in the platform to connect lessons (c.f. **Figure 1**). This process also helped us identify challenging areas for students (or pain points) where deeper cross-linking of concepts would support student remediation.

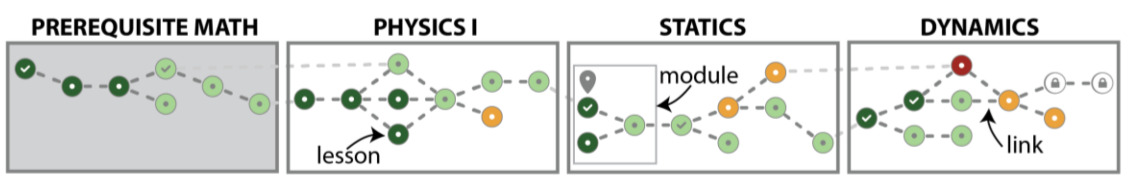

Figure 1. Spine conceptual architecture. Shaded prerequisite material supports concepts in the core spine. Individual lessons, modules of related topics, and links between concepts and courses are shown. Colors suggest the student mastery (green, yellow, red) and progress (color or lock) analytics available to students and instructors.

Following network mapping, we began creating the lessons in the platform, including ingesting existing materials and writing new materials where needed. AL courseware included learning content (lesson materials), concept quizzes, and algorithmic capstone homework problems. Concept quizzes included short numerical or conceptual multiple choice problems. Capstones encompassed multipart scenario problems that include interactive free body diagrams and algorithmic scenarios that allowed each student to receive different numerical scenarios. In addition, interactive external elements, such as Geogebra activities, were embedded to allow open ended exploration of concepts. In some cases, new problems and figures were needed to create larger problem banks, improve figure clarity, and to allow for algorithmic delivery; for example, figures needed to have symbolic rather than numerical annotations. Overall, 190 lessons and 1900 interactive problems were implemented.

In addition, we worked with university learning technology specialists to implement LTI integration between Realizeit and the learning management system to allow grades to be passed natively between systems. Adaptive courseware rules were configured for each course, including semester timing, student access, due dates, and grade weighting. We deployed these materials in Spring 2021 to 1224 students at North Carolina State University in the three sequence courses.

System layout and interactions. Each AL module is built to provide students with the opportunity to engage in individualized learning paths. Students are encouraged to complete a "determine knowledge" quiz at the start of each module, which aids the system in understanding students' current knowledge level for module lesson nodes and plan the optimal place for each student to begin learning. As the student progresses through the lesson nodes, the system updates itself, mapping out a personalized learning path and suggesting what students should tackle next. Students can see a snapshot of their progress via the course overview page. This dashboard provides them information on knowledge covered (number of activities completed), mastery level and overall score, as well as time spent on the course. From here students can navigate to each module where they can view their learning map (**Figure 2**), a personalized visualization of a module and its nodes that guide students to focus on what they don't know yet or struggle with via suggestions and color-coded icons. The system promotes multiple interactions with material as students progress through the use of different learning modes: 1) Revision (revising a lesson node in its entirety without impacting grade), 2) Practice (revisiting a question section from a lesson node without displaying content), 3) Quick practice (revisiting a select number of questions from a lesson node), and 4) Practice module (intended as exam prep, providing questions from all lesson nodes in the module). When working in the lessons, students can bookmark, highlight, or annotate important sections. Further, as they complete questions they can flag the item and query the instructor for clarification. Student grades are automatically transferred to the course LMS at the set due date. Student scores within each node/module represent a combination of 1) progress (how complete modules are), 2) mastery (how well students perform across all lesson nodes), and 3) effort (time spent practicing or revising). Progress and mastery are collectively weighted to approximately 90% and effort 10% of the score.

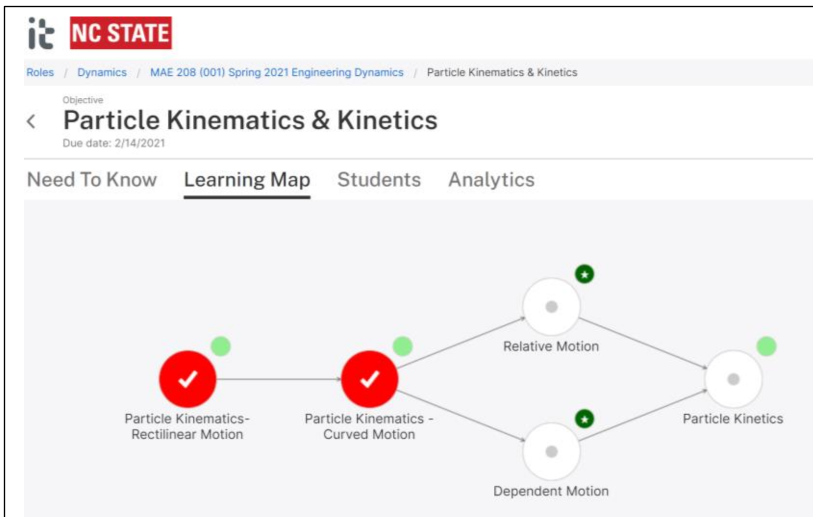

Figure 2. Each student sees their individual mastery and progress in learning maps for each module. Small colored circles represent overall course mastery, while the large circles are the mastery and progress of the specific student.

The AL software also allows faculty to view their course from multiple perspectives via an interactive dashboard. Faculty can view the learning map for each module (**Figure 3**) and summaries for the whole class or each individual student for the major success metrics of 1) mastery, 2) progress, and 3) attitude (**Figure 4**). The view can be toggled to highlight a) those who have started, b) those repeating, c) weaker students, d) stronger students, e) those lagging behind, f) those working ahead, g) those who have not started, and h) those who have finished. In addition, student performance and attempts on individual questions are available to aid faculty in discerning which questions are effective or, alternatively, require additional support or improvement. Analytics are also available by module, lesson, or question to understand student activity in each module, including time spent, overall mastery, and progress. Faculty are also able to monitor student activity, correspond directly with students, and manage course settings. Messages can be sent to students individually or in groups according to their progress, mastery, or emotional state.

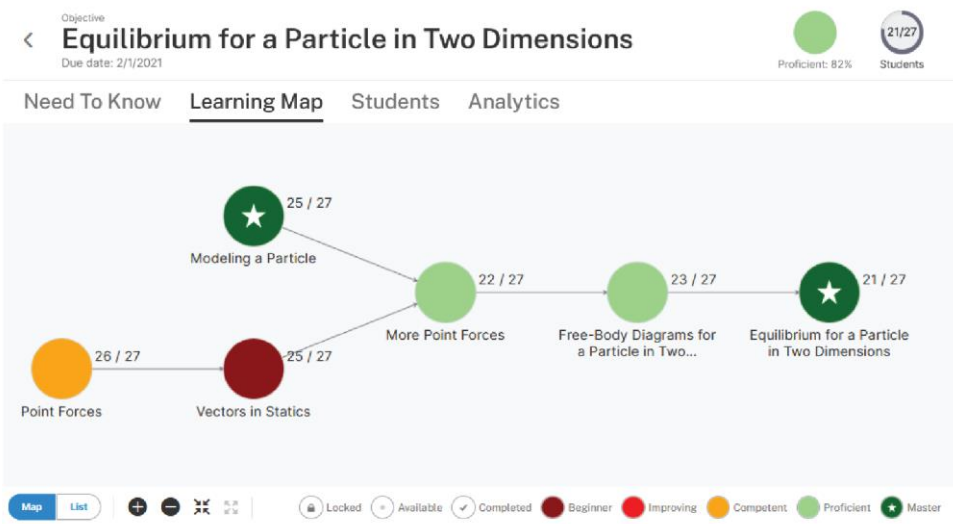

Figure 3. Illustration of a learning map connecting lessons in a module. The faculty view shows overall class mastery (colored circles) and progress (e.g. 25/27 students completed).

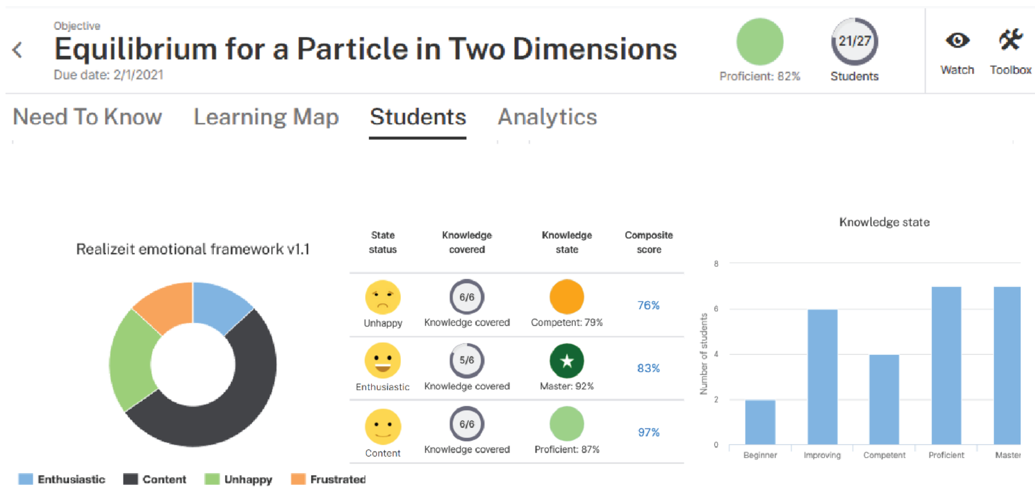

Figure 4. Example analytics available in the instructor dashboard showing student emotional state (left and center, emojis), progress (center, partially filled circles), and mastery (center, colored circles; right).

Evaluation. Institutional review board approval was obtained and informed consent provided prior to data collection. Our evaluation of the project focused on two main areas: 1) faculty reflections on their experience during sequence development and module deployment, and 2) student perceptions, experiences, and course outcomes associated with module use. The first area was examined using a faculty survey administered at the end of the semester. For the second area, we focused specifically on the Dynamics course (130 students) as weekly AL modules were required for a grade, and students had access to AL prerequisite materials as part of the sequence design. Evaluation was achieved through student surveys administered in the first three weeks of the semester (pre-survey) and two weeks prior to the exam period (post-survey), as well as AL (Realizeit) analytics and grade data collated following semester completion.

Specifically, the faculty survey included:

- *Background information on the course* (how often the course is taught, previous experience teaching the course, and pain points in the course/goals for addressing them).
- *Development of the AL modules* (time spent developing AL modules and whether faculty felt it was worthwhile).
- *Experiences implementing the AL modules* (how AL modules were used in the course and time spent administering them, whether teaching approach changed based on AL module use, if faculty felt AL modules supported the other learning materials in the course, level of integration of AL modules in their course).
- *Interactions with the AL software across the course of the semester* (usefulness of available analytics and if faculty used them to inform their teaching, AL software integration with LMS, dashboard usability, use and helpfulness of learning map during course).
- *Future use of the adaptive learning modules* (Continuing use of AL modules, ways to improve AL modules).

The student survey provided to the Dynamics students addressed comfort with engineering and AL technology, and perceptions of the content and platform. Survey areas included:

- Comfort with Engineering
- Comfort with AL technology
- Satisfaction with AL modules
- Clarity and detail of information provided in AL modules
- Clarity of AL module expectations
- Perceptions of AL modules’ ability to aid student learning
- Perceptions of AL modules’ impact transitioning to a college-level course
- Perceptions of the level of integration of AL modules in their course
- Whether students would like the inclusion of more AL modules in a) their current course and b) in other courses they take.

AL analytics included:

- Student engagement in platform
- Activity completion, progress, and mastery

The Spring 2021 Dynamics course had graded elements including the Realizeit AL modules, 3 exams, and an engineering design project that drew from the dynamics concepts and culminated in a multipart design report. Grade data for the 130 students thus included:

- Realizeit component grade
- Final exam grade
- Project grades

In addition, a prior offering of the Dynamics course by the same instructor in Spring 2019 did not include AL modules. Instead, traditional concept quizzes and paper homeworks were used, along with the same exam and project elements. These graded elements for 127 students enrolled in that semester were also evaluated for comparison.

Survey results were evaluated using descriptive statistics. AL analytics including individual module composite scores and engagement metrics were related to course and exam grades using pairwise linear regression and predictive modeling methods to identify the most influential metrics. Predictive modeling methods were implemented in R using a recursive partitioning for a classification tree based on [16]. In addition, linear regression was used to evaluate whether cumulative Realizeit activity scores were associated with student exam or project grades. Similarly, linear regression was used to evaluate in the prior semester whether quiz and homework scores were associated with scores on the other graded elements.

Results

Faculty perceptions. Faculty data showed overall positive perceptions of, and interactions with, the AL module technology. All faculty indicated they would be willing to participate in similar AL projects in the future. With regard to development, faculty reported devoting 5-10 hours/week each during the implementation semester (Fall 2020) spent solely on platform implementation, meetings, quality testing and debugging prior to use of the materials in Spring 2021. An additional 5-10 hours per week during the deployment semester was also required for testing and debugging given the build timeline. It should be noted that this is a separate time commitment from writing the material and problems, as the lead faculty had substantial material prepared prior to initiation of the project. In addition, other personnel were supported by the project to enable development, including platform implementation support from Realizeit, and graduate student (for quality testing) and media creation (for image and video creation) support.

Faculty reported students were more aware of concepts requiring support and asked more pertinent questions. For example, one faculty member reported that students tended to approach them proactively early in the semester with specific concept questions, and that students were more aware of their strengths and weaknesses overall. In addition, faculty perceptions were most positive when AL materials were graded elements that substantially replaced non-AL course material compared to when they were used to supplement existing course materials.

In Dynamics, specifically, the faculty member indicated that the AL modules impacted their teaching approach, affording them the opportunity to engage in a higher level of material-related student interactions as opposed to more administrative tasks such as low-level (homework/quizzes) grading. For example, the faculty member stated that more time was spent engaging on the design project element of the course associated with deeper student thinking because the students were strengthening their fundamentals in the AL platform, and the instructor had more time to spend on higher level topics. Further, they felt the AL modules supported other learning materials in the course and were well-integrated both within their course structure and within their LMS. This faculty member also reported using AL module analytics to inform their teaching, finding them extremely useful and the faculty dashboard easy to use. Additionally, they also revealed that they found referring to the learning map as very helpful to their teaching to identify challenging concepts and students who required attention.

Student perceptions. Evaluation revealed overall positive student perceptions in Dynamics. Student comfort with engineering improved from 81.1% to 87.5% pre- to post-course. Comfort with the AL technology increased from 60.5% to 87.5%. Overall post-course perceptions of the AL technology were positive; satisfaction with the technology was expressed by 70.8% of students, and 83.3% found it helped them master skills. In addition, 91.7% found that the AL modules were well integrated into the course, and 75% showed a preference towards other courses using AL modules. Importantly, relevant to implementation within a course sequence, 75.0% found it helped make connections between prior and new knowledge, and 79.2% found it somewhat, very or extremely helpful to transition into the dynamics class.

Student comments mirrored the quantitative scores. “I liked that the learning content was aligned with [the instructor’s] commentary and in class teaching.” “Realizeit made learning more personal, while other platforms can easily make learning sterile” “The learning map along with the composite grade made it very easy to track progress.” “Step by step learning in the modules made understanding the material much more manageable” Student feedback also exposed the need for more examples and practice questions to be implemented in the problem bank.

Analytics and grades. Engagement analytics revealed that students in Dynamics spent a substantial 2946.7 hours in the AL platform and completed 39,000 total questions (22.7 hours and 300 questions per student on average). This was approximately 6 times as many problems per student as would have typically been assigned as homework in a non-AL semester. Students

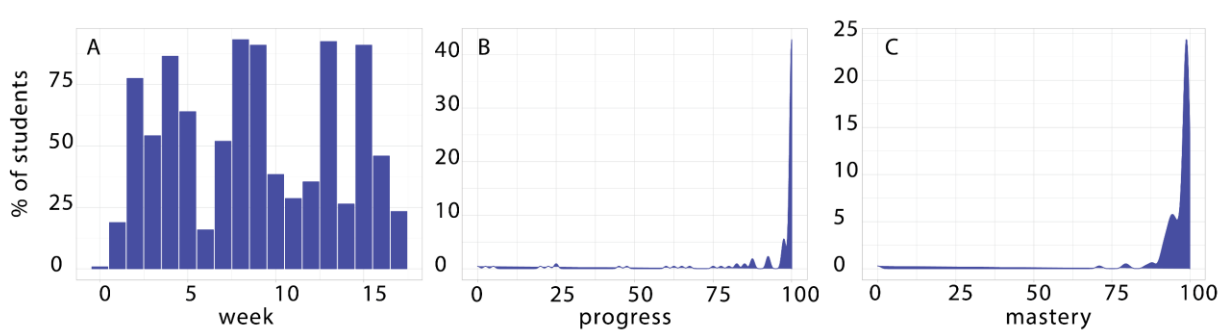

Figure 5. Engagement, progress, and mastery. A) Percent of enrolled students actively participating in a given week shows that students accessed the material consistently throughout the semester. B) Percent of students making progress towards completing all modules in the course. Nearly all students in Dynamics finished all modules. C) Percent of students achieving different levels of mastery, showing that most students were able to achieve mastery of concepts in the course.

accessed the platform consistently throughout the semester and nearly all students ultimately achieved mastery in the modules and completed all modules (**Figure 5**).

The relative importance of analytics variables in predicting students' final course grade revealed that the number of days a student engaged in the platform was the most influential predictor of final grade (**Table 1**). Values are scaled such that total importance sums to 100. A high positive value for variable importance in the predictive model means that the variable is highly predictive. It does not mean that a higher value for the associated variable predicts a higher grade. In fact, there could be some negative or nonlinear relationships. Composite score in the final module learning content (covering 3D dynamics concepts) and first module's capstone problems (covering particle concepts) were also of high importance.

Table 1. Variable importance

Variable	**Importance**
Number of days in platform	14.8
Module 5 Learning Content	12.8
Module 1 Capstone	11.5
Number of activities completed	8.5
Total time spent in platform	7.3
Module 1 Learning Content	7.0
Module 4 Capstone	6.9
Module 3 Learning Content	6.7
Module 2 Capstone	6.0
Module 2 Learning Content	5.1
Module 3 Capstone	4.6
Module 5 Capstone	4.5
Module 4 Learning Content	4.2

In the Spring 2021 Dynamics course, scores on the learning activities in Realizeit were significant predictors of a student's project and exam grades ($p<0.0001$). Notably, 48% of the variation in project grades and 20% of the variability in exam grade was explained by the Realizeit score (as determined by the r^2 from linear regression). In contrast, in 2019 when no AL materials were used, neither homework ($r^2=0$, $p=0.93$) nor quizzes ($r^2=0.02$, $p=0.07$) were significantly associated with the project grade. Both quizzes ($r^2=0.05$, $p=0.015$) and homework ($r^2=0.09$, $p=0.0009$) were significantly associated with the final exam grade, but markedly less of the variability in exam score (5% and 9%) was accounted for by the assignment grades as compared to the AL scores in 2021 (20%).

Discussion

The completed work was the first step towards a transformed, aligned, and personalized engineering mechanics curriculum based around interconnected AL courseware and adaptive pedagogy. Our results suggest that AL can enhance connections in the introductory mechanics sequence and support learning that translates to performance in other graded elements such as projects and exams. Importantly, both faculty and students had positive perceptions of the platform itself, its impacts on engineering understanding, and engagement and alignment in the course. However, our analyses also emphasize that adaptive content and assessments must be considered in course design. Specifically, we note that AL modules are most successful and valuable to students when graded practice elements are replaced by AL elements and the overall course is aligned with the use of AL assignments. AL material must be required and compose a significant portion of the course grade for students to engage consistently with the courseware. In addition, this ensures they will receive the necessary feedback and guidance from the platform and the instructor in order to realize the benefits of the adaptive interface and personalized guidance. Future offerings of the courseware should emphasize tighter integration of courseware with overall course design. In addition, student feedback revealed the need for a large scope of practice questions to enhance student learning; high levels of student activity and questions completed reinforce this need, suggesting at least 6 times the number of questions prepared for a typical course should be implemented to reduce or eliminate question repetition.

Faculty engagement with the platform during course deployment was also critical to ensuring a smooth student experience and providing engagement between faculty and students that enhances both faculty and student perceptions. Professional development training for new faculty users with regard to the dashboard will enhance faculty use of analytics tools. Large classes in which high numbers of students are challenging to manage may require multiple faculty or TA users to make best use of the analytics and engagement tools so that student and faculty interactions can be preserved.

Our experience with AL motivates additional future work to better integrate and evaluate the materials. Future efforts are focused on strengthening the course spine by enhancing interconnections between courses and adding additional course materials. For example, multiple modalities (images, text, video) are critical to reach all student learners; we have implemented multiple media formats and links to external interactive activities (such as Geogebra activities) in some of the content but plan to expand use of these materials throughout the course spine. Additional worked examples, supportive hints, solutions and explanations, and concept links across the spine will be implemented. For example, we have implemented direct prerequisite math knowledge checks and augmented refresher lessons that will automatically be served to students as relevant to the mechanics concepts. We also plan to use the spine structure to enable tracking of concept retention throughout the curriculum. By using standardized questions that will appear in all courses in the spine, we will be able to track whether prerequisite concepts are retained. Finally, we plan to use the current work as a basis by which we can support wider adoption of AL materials in our curriculum and university system.

A notable limitation to the current study evaluation was the current context in which the classes were offered. These materials were developed rapidly in response to the Covid-19 pandemic, and the Spring 2021 offering was fully online with synchronous lectures over zoom. Although we would have liked to more deeply compare student performance and grades with AL materials to prior semesters taught by the same instructor without AL materials, marked differences in the course structure and context made it inappropriate to make such comparisons. For example, the Spring 2020 semester was shifted from in person to online midsemester which led to upheaval for the students and faculty. In addition, many students experienced challenges associated with the ongoing pandemic, illness, online learning, and other factors during the 2021 semester. For this reason we chose to evaluate prior data from Spring 2019, which was a typical in-person semester with no AL materials or interruption, and only evaluated relationships between graded elements within a semester rather than directly comparing grades between semesters. Even so, the differences in course and exam delivery between the semesters evaluated here should be considered. In future, quantitative data from AL analytics, course records, pre- and post-surveys and instruments will be compared between sections offered with and without AL materials, across semesters, and across courses after continuous improvements.

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