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Adaptive Learning At Scale*

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Current Issues in Emerging eLearning

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Volume 7, Issue 1 (2020)

Special Issue:

Implementing Adaptive Learning At Scale

CURRENT ISSUES IN EMERGING ELEARNING

Special Issue on Implementing Adaptive Learning At Scale

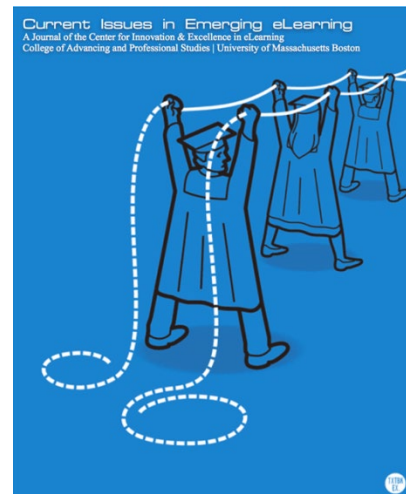
Volume 7, Issue 1 (2020)

GUEST EDITOR

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Personalized Learning Consortium

Association of Public & Land Grant Universities



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Current Issues in Emerging eLearning

Volume 7, Issue 2(2020) Special Issue:

Implementing Adaptive Learning At Scale



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FOREWORD:

IMPLEMENTING ADAPTIVE LEARNING AT SCALE

A SPECIAL ISSUE OF *CIEE* JOURNAL SPONSORED AND GUEST EDITED BY
THE PERSONALIZED LEARNING CONSORTIUM
ASSOCIATION OF PUBLIC AND LAND-GRANT UNIVERSITIES

Karen Vignare, Ph.D, Executive Director
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What follows is the second of now two Specials Issues of the *CIEE* journal to have been produced and guest edited by the Personalized Learning Consortium (PLC) of the Association of Public and Land-grant Universities (APLU). Both special issues feature important research resulting from university initiatives to launch, implement and scale up the use of adaptive courseware and the strategies of adaptive learning.¹ The Personalized Learning Consortium has been working with institutions for more than five years to improve student success in high enrollment undergraduate courses. Using a combination of active learning and adaptive courseware, many universities are reporting higher passing rates but also more equitable outcomes. In this issue, we share five papers that discuss how and why higher education institutions have incorporated adaptive courseware and learning into high enrollment general education courses. The papers also provide detailed examples of levels of success achieved.

The papers in the journal issue include work from five institutions: Arizona State University, Colorado State University, Portland State University, University of Central Florida, and University of Mississippi. One paper describes a shared approach to implementation of adaptive courseware in a biology course at each institution, as well as an additional case study from each institution in a course of their choice, such as chemistry, physics, and Spanish. Student survey and outcomes results are included throughout the case studies. This paper also addresses what benefits and barriers students perceived when using adaptive courseware, along with how the alignment between adaptive courseware and course organization and structure impact student experience. Throughout the papers, the multiple authors also offer research questions for further investigation of adaptive courseware and learning.

¹ The first of now two PLC-sponsored *CIEE* journal issues, published as Volume 5, Issue 1 (2018) Special Issue on Leveraging Adaptive Courseware, remains freely accessible and downloadable.

In “Designing and Teaching Adaptive+Active Learning Effectively,” van Leusen, Cunningham, & Johnson (2020) present adaptive+active learning as a transformative initiative, the success of which depends upon taking a system approach. The paper refers to an adaptive courseware implementation at Arizona State University (ASU), where several high-enrollment general education courses were changed from a lecture-based model to an instructional model that focused on design choices and teaching practices in which the technical capabilities of adaptive courseware were aligned to active learning techniques.

ASU’s implementation under this instructional model began in 2014 when ASU partnered with adaptive courseware vendors for an introductory algebra course, a beginning biology class, and two U.S. history survey classes. In a section of the paper titled “Overview of key facilitation skills,” van Leusen, et al. present two key facilitation skill changes that are needed by instructors for a successful adaptive courseware and learning implementation: use learning analytics to identify struggling learners, and a change in teaching style from lecture-centered to learner-centered. Additionally, “the need emerged to establish a team whose members collaboratively facilitated these changes and supported faculty and departments.” Overall, van Leusen, et al. claim that “the system approach in the adaptive+active instructional model has improved student success at ASU, in particular in large enrollment courses.”

In “A Transformative Approach to Incorporating Adaptive Courseware: Strategic Implementation, Backward Design And Research-based Teaching Practices,” Buchan, Kruse, Todd & Tyson (2020) present a thorough case study of how Colorado State University (CSU) implemented adaptive courseware and learning as a PLC/APLU grantee, starting in July 2016. CSU successful implementation scaled quickly to 11,336 enrollments in targeted high-enrollment, general education courses within two years. As the title of this paper suggests, CSU took a three-pronged “transformative” approach: 1) strategic implementation of courseware, 2) backward course design, and 3) incorporation of research-based teaching practices. The goal was to “promote academic success for all students, but particularly for students from historically underserved groups, since active learning with increased structure has been shown to reduce the achievement gap.”

Buchan, et al. cover CSU’s in-depth approach, including providing information on how to recruit courses for adoption, courseware selection, use of analytics, faculty professional development, the development of faculty learning communities, and how to measure research-based teaching practices. Several interesting tables on student success outcomes also are presented, along with faculty feedback statements and recommendations regarding adaptive courseware. The authors note that “faculty use of research-based teaching practices in strategic alignment with active learning and adaptive courseware provided the greatest measure of success.”

In “Adaptive Analytics: It’s About Time,” Dziuban, Howlin, Moskal, Muhs, Johnson, Griffin, and Hamilton (2020) begin by acknowledging all the challenges our educational system in the U.S. faces, presenting reference to the inequities and struggles confronting underserved students, including working adults who must deal with employee-based pressures en route to earning a degree or even a certificate. The authors present a detailed case study of an effective adaptive learning partnership involving college algebra courses at the University of Central Florida (UCF) and at Colorado Technical University (CTN), courses that have been utilizing an adaptive platform that provides students alternative paths for earning passing grades. The authors also note that, while adaptive learning has been gaining acceptance, “research results have been mixed,” while not enough research has been released by those who have been working on scaling adaptive learning.

Dziuban, et al. explain that “learning analytics research is often institution-specific, examining single-use for prediction of students at-risk that can be difficult to scale and transport beyond their home institutions.” Overall, Dziuban, et al. claim that courseware implementations at UCF and CTU, two institutions “with considerably different infrastructures and student populations. . . indicated that combining adaptive learning and learning analytics offers promise for helping students achieve successful outcomes in college algebra.”

In “Student Perceptions of the Effectiveness of Adaptive Courseware for Learning,” Monroe, O’Sullivan, Forgette, & England (2020) from the University of Mississippi (UM) assessed “student perception of the effectiveness of adaptive learning platforms in courses delivered face-to-face [at UM] and on a variety of adaptive platforms.” The adaptive courseware used in UM courses included Pearson’s Mastering and MyLabs, McGraw Hill’s LearnSmart and ALEKS, Cengage’s MindTap and Open Now, Realizeit, Smart Sparrow, Wiley Plus with Orion, Lumen Waymaker, Hawkes Learning, and Macmillan’s Learning Curves.

Between Spring 2017 and Spring 2019, Monroe, et al. conducted student focus groups and administered student surveys over four rounds; the researchers present their results in this paper. For example, they find that “in all four surveys, respondents identified ‘more flexibility in submitting homework and quizzes’ as the number one way in which the courseware changed how they learned.” Regarding student focus group results, “cost and value was their top concern about adaptive courseware.” Monroe, et al. provide many more significant results garnered from both the surveys and the focus groups. However, “in both the focus groups and the surveys, more students had positive views than had negative views of digital learning platforms. The courseware features students found helpful were generally those that supported learner autonomy, which they valued more than algorithmic adaptability.”

The final paper in this special issue, “Adaptive Courseware Implementation: Investigating Alignment, Course Redesign, and the Student Experience” is a review of active and adaptive learning implementation from multiple institutions: University of Mississippi, Portland State University, Colorado State University, and University of Central Florida. In this paper, O’Sullivan, Voegele, Buchan, Dottin, Kono, Hamideh, Howard, Todd, Tyson, Kruse, de Gruyter & Berg (2020) share the student and faculty feedback gathered from each institution’s separate active and adaptive implementation of biology for undergraduate non-majors. In this paper, four institutions share student and faculty feedback on the implementation of adaptive courseware through a common case study: biology for undergraduate non-majors. Each institution also provided a second undergraduate course implementation case study. O’Sullivan et. al, investigate student perceptions of adaptive courseware. The case studies also address how the deliberate alignment between adaptive courseware, and course organization and structure impacts student experience. The authors highlight the collaboration and benefits of scaling adaptive courseware implementation, operating as cohort of institutions all of whom function as grantees of the 2016 APLU grant.

O’Sullivan et. al. (2020) state that adaptive courseware holds much potential for a more personalized digital learning experience. This paper shares multiyear data from the institutions regarding each of the courses discussed. The cases also demonstrate that incorporating new learning technologies creates opportunities to revisit assumptions about course development and design, and to place student engagement at the center

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Designing and Teaching Adaptive+Active Learning Effectively

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DESIGNING AND TEACHING ADAPTIVE+ACTIVE LEARNING EFFECTIVELY

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ABSTRACT:

To fulfill the promise of providing all learners with access to education, institutions of higher education are exploring personalized learning for individuals with different skills, abilities, and interests. These universities have turned to an instructional model that combines adaptive courseware and learner-centered instruction. This is often referred to as active learning. Despite growth in adaptive courseware and generous support through national organizations, successful implementation of adaptive systems is mixed (SRI Education, 2016). This article highlights the need for a systems approach and illustrates this approach through design and pedagogy decisions that have contributed to the success of adaptive learning at Arizona State University (ASU).

KEYWORDS:

instructional design, systems approach, adaptive courseware, active learning

DISCIPLINES:

Educational Methods, Educational Technology, Instructional Design

DESIGNING AND TEACHING ADAPTIVE+ACTIVE LEARNING EFFECTIVELY

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INTRODUCTION:

To broaden access to education, institutions of higher education have explored the possibility of enabling personalized learning for individuals with different skills, abilities, and interests. Faced with the challenge of scaling personalized learning, adaptive computer-based systems promise to guide learning experiences by tailoring instruction and/or recommendations based on the goals, needs, or preferences of the learner (Graesser, Hu & Sottolare, 2018). Despite the growth in adaptive courseware vendors and generous support through national organizations, successful implementation of adaptive systems is mixed (SRI Education, 2016). This article highlights the need for a system approach and illustrates this strategy through design decisions and facilitation skills that have contributed to the success of integrating adaptive learning at Arizona State University (ASU).

BACKGROUND:

More universities are expanding their mission to provide access to broader audiences. This has resulted in increased enrollment in *General Education* courses as students with diverse backgrounds and learning experiences seek a college education. To ensure student success in large enrollment courses, educational institutions require an instructional model and tools that can be implemented effectively and efficiently at scale for individuals of diverse skills, abilities, and interests. While efficient, lecturing, one of the most common instructional models for large groups, tends to be less effective, often resulting in lower percentages of learner success and retention (Feldman & Zimbler, 2012). Furthermore, to help learners engage and focus their efforts on striving to attain the desired learning outcomes, educational institutions need to develop instructional activities that motivate individuals and groups, make materials relevant, and foster employability skills (soft skills).

A SYSTEMS APPROACH:

To identify an instructional model including tools that meet the specific needs of introductory courses with large enrollments at ASU, a team composed of faculty, instructional designers, technologists and other support personnel approached the design, development, and implementation of the new solution from a systems view - wherein organizational and instructional systems are related and changes to one element impact other elements or even sub-systems (von Bertalanffy & Rapoport, 1956). Developers of the initiative discussed herein surveyed key stakeholders and their contexts, and aligned the initiative with ASU's overall charter of student success. The needs assessment indicated that the new instructional model should combine the implementation of adaptive courseware with active learning techniques.

DESIGN

Instructional Design is the systems approach to creating effective, efficient, and engaging instruction. It is the framework for developing learning experiences [programs, courses, modules, units, lessons, etc.], which promote the acquisition of specific knowledge and skills (Merrill, Drake, Lacy & Pratt, 1996). Although learning theories, such as behaviorism, cognitivism, and constructivism, generally describe learning and provide considerations for motivating individuals, learning theories generally lack concrete guidelines for designing learning experiences (Ulrich, 2008). Here, more prescriptive models or practices derived from instructional design models provide more guidance. For example, Engelmann's *Direct Instruction* (National Institute for Direct Instruction, 2015), which is deeply rooted in the learning theory of behaviorism, provides concrete sequences and steps on how to engage with learners. While effective and efficient under certain circumstances, a sixty-minute lecture can become less engaging and can lead students to disconnect quickly. In contrast, combining *Direct Instruction* with other models, such as problem-based learning, can lead to higher levels of engagement while also ensuring effectiveness (Winarno, Muthu & Ling, 2018).

Although it might be challenging to identify a single theory or instructional model that describes learning for all learners in all contexts, Ertmer and Newby (1993) explained that "as one moves along the behaviorist-cognitivist-constructivist continuum, the focus of instruction shifts from teaching to learning, from the passive transfer of facts and routines to the active application of ideas to problems" (p. 58). Instead of focusing on which learning theory might be best to design the learning experiences, one should consider the task to-be-learned including the audience and contexts. In other words, an instructional model is needed that is eclectic in nature and considers the various types of learning that can occur throughout a course.

One attempt to identify instructional models that supersede individual learning theories was conducted by David Merrill (2002). Merrill's *First Principles of Instruction* are "a set of principles that can be found in most instructional design theories and models and even though the terms used to state these principles might differ between theorists, the authors of these theories would agree that these principles are necessary for effective and efficient instruction" (p. 44). Beyond subject matter, context, and learner background, Merrill identified five principles which provide guidance on designing effective, efficient, and engaging instruction.

The following comprise Merrill's five principles:

1. Learning is promoted when learners are engaged in solving real-world problems
2. Learning is promoted when existing knowledge is activated as a foundation for new knowledge
3. Learning is promoted when new knowledge is demonstrated to the learner
4. Learning is promoted when new knowledge is applied by the learner
5. Learning is promoted when new knowledge is integrated into the learner's world

Considering real-world problems to be at the very core of learning experiences, Merrill further suggested sequencing instruction through the iteration of four individual phases - activation, demonstration, application, and integration.

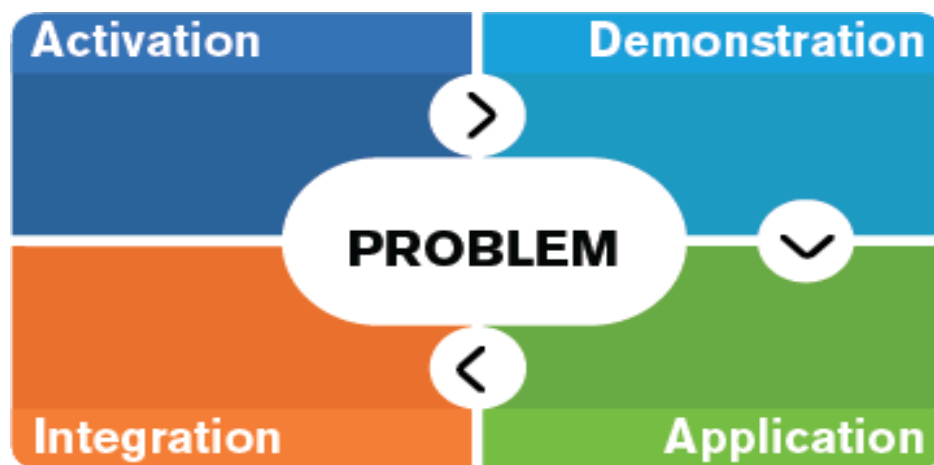


Figure 1. Phases of Effective Instruction, Merrill (2002)

Fundamental to Ertmer and Newby's arguments as well as Merrill's principles is the concept that there is a taxonomy of learning and that learning requires different tasks. According to Bloom's taxonomy (Bloom, Krathwohl, & Masia, 1984), learning can be broken down into various levels which become increasingly more difficult. For example, *seeing someone* drive a car [demonstration] does not necessarily imply that one *can* drive a car successfully based simply on having witnessed the act [application].

Furthermore, moving across the behaviorist-cognitivist-constructivist continuum as called for by Ertmer and Newby, the question arises which tasks can best be learned individually and which can best be learned collaboratively with peers? Cognitive science suggests the need to have learners actively involved in their own learning, – an idea further supported by Micki Chi's ICAP framework (Chi, 2009). Chi conducted a meta-analysis of educational research studies and determined that *active learning*, in which learners engage with peers or experts in dialog around an overt learning task, is more effective than passive learning. Recognizing that there is a taxonomy in which effective learning can be broken into individual and collaborative activities is particularly important to instructors and instructional designers as they create environments in which learning needs to be assessed (Chi, 2009, p. 76).

TEACHING

In addition to an instructional model applicable across diverse contexts, subjects, and audiences, the implementation or teaching of the design is an equal, if not more important, aspect of successful instruction. In short, teaching comprises the implementation of the design as well as the "... process of attending to people's needs, experiences and feelings, and intervening so that they learn particular things, and go beyond the given" (Smith, 2019, para. 2). The facilitator needs to be able to design learning activities and instructional interventions to enable student success and needs to recommend appropriate activities to help learners achieve the learning objectives.

Chickering and Gamson's *Seven Principles of Good Practice in Undergraduate Education* (1987) is one of the most prominent sets of educational practices for effective and engaging teaching in higher education. Drawing from over fifty years of education research, the principles highlight the contact between learners and faculty, the importance of engagement, and the need for meaningful feedback in a timely manner.

Specifically, the seven good practices Chickering and Gamson advocate are as follows:

1. Encourage contact between students and faculty
2. Develop reciprocity and cooperation among students.
3. Encourage active learning.
4. Give prompt feedback.
5. Emphasize time on task.
6. Communicate high expectations.
7. Respect diverse talents and ways of learning.

While these practices are proven to be effective, one needs to carefully examine the time, educational contexts, and audiences that were in place when these principles were developed. Certainly, society, audiences, and tools have changed since 1987. For example, today's learners can enroll in more modalities to pursue an undergraduate or graduate education such as online education. The principles may apply to online learning with studies examining their applicability to technologically-driven learning environments (Chickering & Ehrmann, 1996); however, the changes in society in the past 20 years due to rapid developments in technology need to be examined. Considering the changes in how we communicate and access information, one will need to expand on these principles.

Among those considerations is certainly the teaching of large enrollment courses due to increased access to higher education. According to the National Center for Educational Statistics (NCES, 2019), the undergraduate enrollment in degree-granting postsecondary institutions was 19.8 million learners in 2016, an increase of 12% from 2006 (17.8 million). Similarly, we see a more diverse population today than ever before (NCES, 2019) when, for example, it comes to age, ethnicity, and educational preparation. While broader access to education is much needed, the consequences of larger and more diverse classrooms require rethinking well-established teaching practices and principles. From an instructor perspective, a common challenge is to recognize who among the learners needs assistance with what concept or skills. In short, it is important to identify struggling students as early as possible so one then can administer appropriate interventions to help students succeed.

ADAPTIVE+ACTIVE LEARNING INITIATIVE AT ARIZONA STATE UNIVERSITY

The promise of student success through personalized learning resonates with the core values of ASU, a large public research university (~100K students). The university's charter states that "[we are] measured not by whom we exclude, but rather by whom we include and how they succeed."

In 2014, the university's leadership identified several high-enrollment *General Education* courses that consistently showed low retention and performance rates (e.g., introductory biology, psychology, college algebra). After extensive design and development, these courses were transformed from a traditional lecture-based model to an instructional model in which instructors and students harness the benefits of adaptive courseware and learner-centered pedagogy (active learning). As part of this large initiative, ASU partnered with adaptive courseware vendors to design, develop, and implement an introductory mathematics course (College Algebra), a beginning biology class, and two U.S. History survey classes. Under the leadership of the Adaptive Program Director and in collaboration with ASU departments and faculty, a cross-functional team consisting of instructional designers, media developers, technologists, librarians, and vendor personnel initiated the development of these courses.

This adaptive+active instructional model has significantly increased the student success rate in *General Education* courses enabling thousands of additional students to advance toward their degree (see figure 2). It also has provided ASU faculty and staff with unique insights and expertise regarding how to deliver on the promise of personalized learning at scale in education. By 2019, what began with pioneering work on an introductory mathematics class had grown to include over 25 courses across seven different disciplines enrolled by more than 90,000 students. In the academic year 2019-20, ASU projects that close to 27,000 students will enroll in a course that uses an adaptive+active instructional model.

Although the needs assessment identified additional interventions to support student success, including implementing effective student support and advising processes, this paper focuses on the instructional implications, in particular the design choices and teaching practices ASU has adopted.

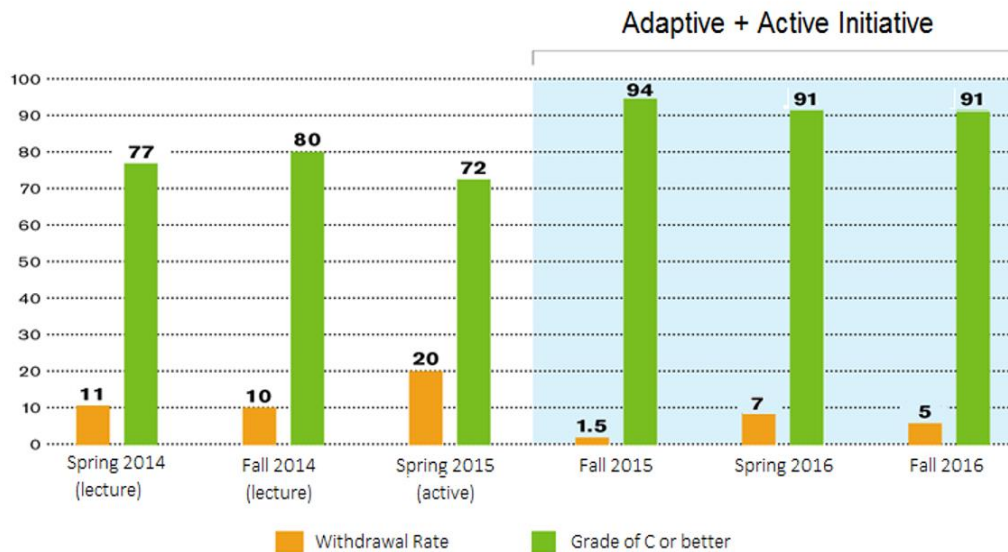


Figure 2. Student success data in *Introductory Biology* with approx. 400 students, same instructor.

OVERVIEW OF KEY DESIGN DECISIONS:

To accomplish those transformations successfully, the ASU team closely examined the learning objectives of each course, identified matching assessments, and considered aligned instructional activities and resources. Furthermore, drawing from Ertmer and Newby's (1993) eclectic model as well as Chi's (2009) framework for interactive learning, objectives were identified, which were better suited for individual learning versus collaborative learning. As a result, learning objectives associated with lower levels of Bloom's Taxonomy (1956), such as remembering or understanding, were identified as being appropriate for individual learning, while learning objectives associated with higher levels, such as analyzing and creating were identified as being appropriate for collaborative settings.

Considering the challenge posed by large enrollment and diverse learner backgrounds, the model needed to deliver the right lesson to the right student at the right time. Here, the affordances of adaptive technology allowed each individual learner to engage with course materials matching their level of understanding. As learners interact with the adaptive courseware, key concepts and skills are being activated, demonstrated, and - at a fundamental level - applied (Merril, 2002). In addition, learners receive immediate feedback fundamental to Chickering and Gamson's *Seven Principles of Good Practice in Undergraduate Education* (1987).

Upon mastering lower level objectives in the adaptive courseware, students engaged in active learning activities that addressed higher level objectives. These learner-centered teaching activities tend to foster reflection, enable collaboration, and increase student performance (Freeman, Eddy, McDonough, Smith, Okoroafor & Wenderoth, 2014).

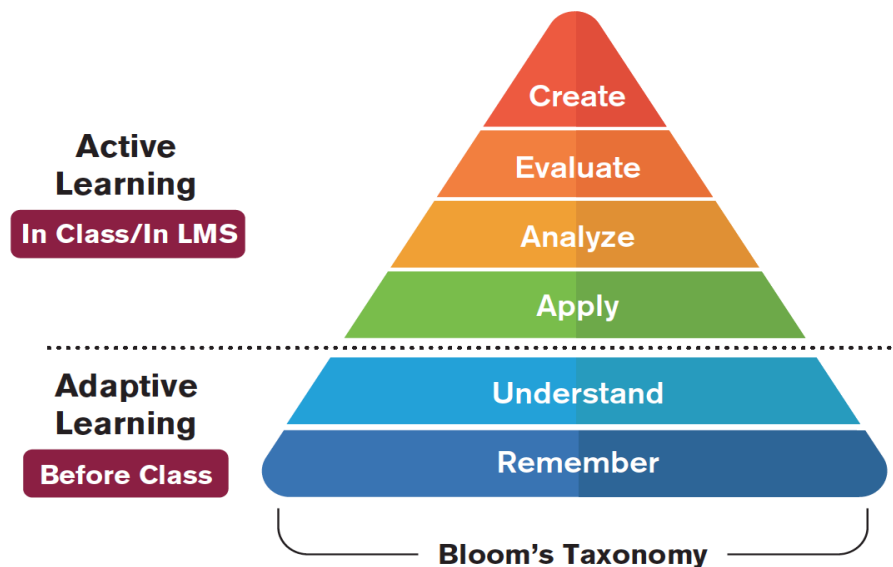


Figure 3. Adaptive+Active Learning aligned with Bloom's Taxonomy

To implement these concepts successfully, the following transformations were needed in the instructional model, course facilitation and technology:

1. Courses were designed so that the adaptive delivery of instructional resources increases learner access to the learning materials and frees up time for instructors to lead students through active learning exercises.
2. Instructional materials and activities in adaptive courseware focused on fundamental concepts and skills. Learners achieved the mastery level defined by the faculty through individualized instruction and rapid remediation.
3. Learning analytics from the adaptive courseware improved instructor insight into each learner's mastery. These insights allowed the instructor to implement a choice of instructional interventions based on individual needs.

4. Outside the adaptive courseware, active learning exercises were employed to deepen learner understanding of fundamental concepts and skills. Instructional materials and activities further addressed so-called 21st Century Skills (National Education Association, 2019) and employability skills (e.g., critical thinking, communication, collaboration, problem-solving).
5. Adaptive+active course creation was a team effort to ensure the effective design, development and facilitation of the new approach. For example, the team included at least two faculty members to lead the effort. One instructional designer provided teaching and learning support as well as coordinated the work with multimedia developers, web technologists, evaluators, and external partners. Finally, one project manager coordinated the adoption process through at least the first three iterations of the course to ensure the effective and efficient transition for learners and instructors.

It is important to note that this instruction model is flexible and applicable across modalities. On campus, this is implemented as a “flipped” model (Bergman & Sams, 2014) with the learners working in the adaptive courseware before class to prepare them to do active learning in class. Online, the same adaptive courseware is used to deliver the instruction, and the active learning is done using other digital tools, such as discussion forums and web collaboration systems.

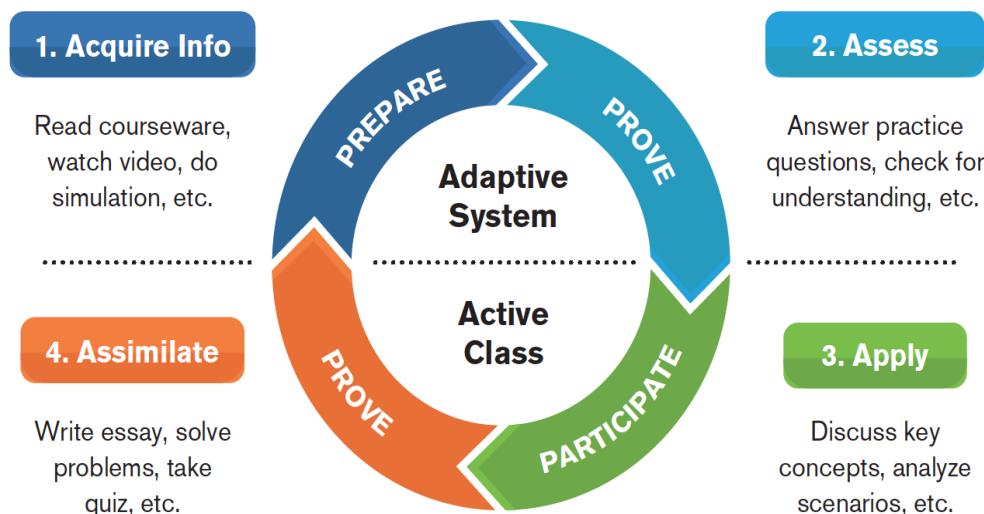


Figure 4. Roles of adaptive courseware and active learning

THE ROLE OF ADAPTIVE COURSEWARE

Adaptive courseware are technical platforms that "dynamically adjust [learning materials] to student interactions and performance levels, delivering the types of content in an appropriate sequence that individual learners need at specific points in time to make progress" (ELI, 2017, p. 1). Specifically, adaptive courseware deliver instructional resources (videos, texts, examples, exercises, etc.) and formative assessment activities (multiple choice, matching, fill in the blank, etc.) to help students master the learning objectives of each lesson. Consequently, students enrolled in the same course might have different, but more personalized experiences in a course that employs adaptive learning courseware.

Adaptive systems are nothing new; however, recent technological developments, such as a better understanding of learner behavior and knowledge through data analytics, now allow designers of these systems to develop algorithms that adapt assessments, feedback, content, and various media to individual students (ELI, 2017). The systems collect data on learner performance and progress in order to recommend lesson(s) and/or resource(s) to help each student learn as effectively and efficiently as possible. Techniques such as assessment, algorithmic analysis, agency (student feedback), and association (lesson mapping) are used to guide these recommendations.

THE ROLE OF ACTIVE LEARNING

Subsequent to engaging in individual learning activities within adaptive courseware, when in-class or online within the Learning Management System, students participated in active learning exercises that targeted higher order thinking and also helped learners develop professional skills such as critical thinking, communication, collaboration, and creativity. These exercises varied in scale and scope depending on the nature of the lesson, the amount of time available, and learning objectives of the faculty member. In general, learners were grouped into teams using various techniques (lesson progress, previous grades, random assignment, etc.) and guided through the exercises by their instructors.

Key to the development of the active learning experiences was the 5E Instructional Model by Bybee (1987). Developed as part of a Biological Sciences Curriculum Study, the 5E Model has learners collaboratively solve applied problems and investigate concepts and skills as they progress through a sequence of scaffolded learning activities. These activities are *Engage*, *Explore*, *Explain*, *Elaborate*, and *Evaluate*. Furthermore, in a more recent review, Bybee (2009) identified the model as holding the "promise as a general model for effective teaching to develop 21st century skills" (p. 11).

Summary of the BSCS 5E Instructional Model (Bybee, 2009, p. 4):

Phase Summary	Summary
Engage	The teacher or a curriculum task assesses the learners' prior knowledge and helps them become engaged in a new concept through the use of short activities that promote curiosity and elicit prior knowledge. The activity should make connections between past and present learning experiences, expose prior conceptions, and organize students' thinking toward the learning outcomes of current activities.
Explore	Exploration experiences provide students with a common base of activities within which current concepts (i.e., misconceptions), processes, and skills are identified and conceptual change is facilitated. Learners may complete lab activities that help them use prior knowledge to generate new ideas, explore questions and possibilities, and design and conduct a preliminary investigation.
Explain	The explanation phase focuses students' attention on a particular aspect of their engagement and exploration experiences and provides opportunities to demonstrate their conceptual understanding, process skills, or behaviors. This phase also provides opportunities for teachers to directly introduce a concept, process, or skill. Learners explain their understanding of the concept. An explanation from the teacher or the curriculum may guide them toward a deeper understanding, which is a critical part of this phase
Elaborate	Teachers challenge and extend students' conceptual understanding and skills. Through new experiences, the students develop deeper and broader understanding, more information, and adequate skills. Students apply their understanding of the concept by conducting additional activities.
Evaluate	The evaluation phase encourages students to assess their understanding and abilities and provides opportunities for teachers to evaluate student progress toward achieving the educational objectives.

As a final step in the design process, summative assessments had to be updated to reflect the new instructional model. The adaptive courseware and active learning offer numerous formative assessment opportunities in which learners can check their own understanding and receive feedback from various sources (e.g., machine, peers, instructor). To hold learners accountable for those activities and also provide learners an opportunity to be academically successful, the grading scheme was adjusted to reflect the importance for learners to complete all learning materials. While grading schemes differ from course to course, activities in the adaptive courseware generally account for 20% of the final grade, activities and participation in active learning for 40%, leaving another 40% to traditional summative assessments, such as exams and papers.

OVERVIEW OF KEY FACILITATION SKILLS:

The design of the adaptive+active instructional model also required to develop two key facilitation skills. The first skill was the adept use of learning analytics to identify struggling learners in large enrollment courses using adaptive courseware. Due to the digital nature of the adaptive courseware, each learner's activities and performance are tracked. Instructors need to be able to access and interpret these data quickly to ensure proper interventions. The second facilitation skill involved a change of teaching style--the transformation from lecture-style instruction to a more learner-centered, active learning approach. In particular, team efforts focused on defining the instructor role in a "classroom flip model" (Zappe, Leicht, Messner, Litzinger, & Lee, 2009). It also provided "the time and preparation needed to create and deliver [collaborative] activities" (EDUCAUSE Review, 2019, para. 1).

THE ROLE OF LEARNING ANALYTICS

Learning analytics is the practice of using data in the context of education to understand and optimize the learning experience (SOLAR, 2020). Adaptive, personalized educational approaches have been closely tied to the field of learning analytics since the early 1980s when computerized tutors taught coding and geometry using rudimentary artificial intelligence (Anderson & Corbett, 1995). In recent years, adaptive educational software platforms have used sophisticated algorithms to evaluate student background knowledge and respond as students gain mastery of educational concepts or skills (Alevan & Koedinger, 2002; Falmagne, Cosyn, Doignon, & Thiery, 2006). As learners work through course material in adaptive environments, they create unique pathways that are then recorded as data generated by the software. The data produced by learners working in these environments are especially rich because they reflect the unique characteristics of each student engaged in the learning process. This data then can be connected with

student outcomes reflected in formative and summative assessments linking each pathway with student success. These patterns of student success can be recognized through machine learning to develop predictive models.

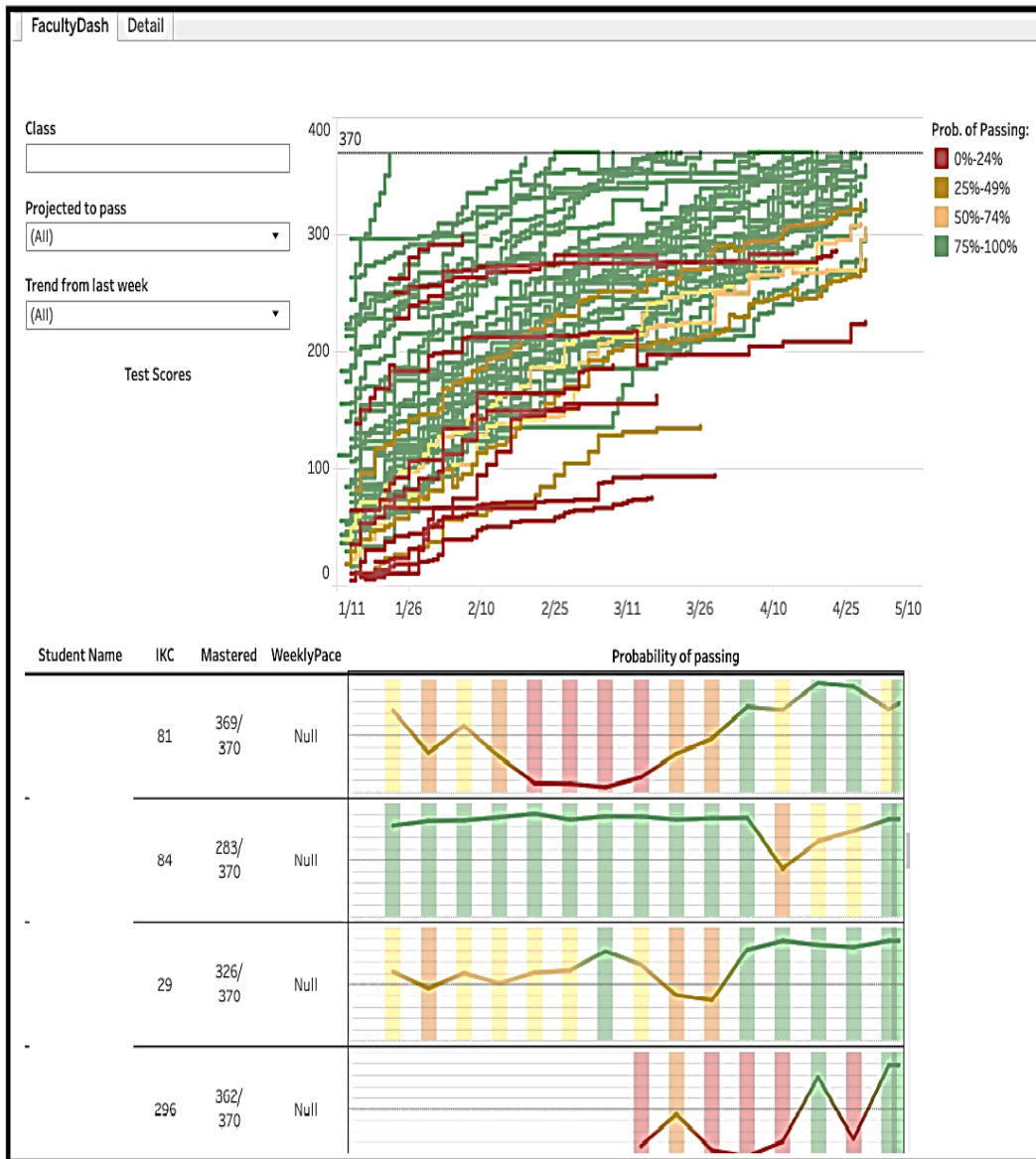


Figure 5. Example of a predictive dashboard being piloted with faculty teaching adaptive *College Algebra* classes. Colors represent varying predictions of student success.

At ASU, ongoing research is leveraging the rich data of adaptive platforms with machine learning to create predictive models of student success based on the outcomes of thousands of students. These predictions are then used to inform instructors early in the term if students are likely to be on a successful path. Because these predictions are early, interventions in the form of additional student support and scaffolding can be employed to improve student outcomes enhancing the adaptive+active instructional model. In addition to predicting student success, learning analytics are being used to evaluate the adaptive platform itself by analyzing student interactions with the software. This analysis highlights weaknesses in the course material or in the presentation of coursework that may need to be improved for greater student learning. Currently, pilot projects have been launched leveraging adaptive data; however this research is in the early stages.

THE ROLE OF THE FACILITATOR

In the adaptive+active instructional model, the facilitator is the key for a successful implementation. Foremost, the utilization of the adaptive courseware requires instructors to align in-class activities with the concepts and skills that students learn before they arrive. Hence, instructors do not need to repeat all the content that was covered in the adaptive courseware. Instead, in-class activities and assessments build upon those materials and focus on higher order thinking. By ensuring that material is not repeated, instructors hold learners accountable for the materials provided through the adaptive courseware. As Allen (1995) points out, "incorporating active learning techniques must be purposeful to carry out specific and important objectives, and must require students to use the higher order skills of analysis, synthesis, and evaluation" (p. 99).

Secondly, the shift from lecture-style instruction to more learner-centered instruction significantly impacts the role of the facilitator. In this model, the facilitator is no longer the only source of knowledge, nor are is the facilitator responsible for transferring knowledge to learners. In contrast, "successful active learning activities provide an opportunity for all students in a class to think and engage with course material and practice skills for learning, applying, synthesizing, or summarizing that material" (University of Minnesota, 2020, para. 1). This shift in classroom management is not straightforward nor can it be done individually. Mabry (1995) explains that instructors need to give up some control, so that students will learn more and retain that knowledge longer. At ASU, facilitators are supported in making this shift successfully through faculty development initiatives, peer coaching, and a continuous review and improvement approach.

CONCLUSION:

The system approach reflected in the adaptive+active instructional model has improved student success at ASU, in particular in large enrollment courses. Fundamental to this instructional model is the complementary use of adaptive courseware aligned with active learning in the classroom or Learning Management System. Beside the instructional model, teaching practices needed to reflect and match this new approach. Utilizing learning analytics effectively to inform potential interventions and implementing learner-centered teaching have been key to the overall success.

To achieve the various transformations listed in this paper, ASU stakeholders identified the need to establish a team whose members collaboratively facilitated these changes and supported faculty and departments. As subject matter experts and facilitators in most cases, faculty were fundamental to the successful design and implementation. In addition, innovative thought leaders and change agents within the institution needed to drive the transformation. Instructional designers functioned as collaborative systems thinkers who had the broad background of learning theories, teaching practices, and the technical knowledge required to design these highly complex learning experiences. Data Analysts provided the analytical mindset and skills needed to make data-informed decisions for instructional use or the evaluation of initiatives. Vendors and multimedia developers offered services that further complemented the team. Additional members, such as librarians and assessment specialists, were also considered for developing high quality learning experiences. As institutions of higher education seek to focus more and more on student success, a collaborative approach with system thinkers is at the very heart of success or failure of these transformative initiatives.

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A Transformative Approach to Incorporating Adaptive Courseware: Strategic Implementation, Backward Design and Research-based Teaching Practices

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A TRANSFORMATIVE APPROACH TO INCORPORATING ADAPTIVE COURSEWARE: STRATEGIC IMPLEMENTATION, BACKWARD DESIGN AND RESEARCH-BASED TEACHING PRACTICES

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ABSTRACT:

In July 2016, Colorado State University (CSU) joined seven other land-grant institutions in the Accelerating Adoption of Adaptive Courseware grant sponsored by the Personalized Learning Consortium (PLC) of the Association of Public and Land-grant Universities (APLU). A primary objective of the grant was to scale the adoption of adaptive courseware in general education courses at each of the grant institutions. CSU targeted high-enrollment, general education courses and took a three-pronged, transformative approach to the integration of adaptive courseware. Specifically, CSU divided the courseware integration into three components: 1) strategic implementation of courseware, 2) backward course design, and 3) incorporation of research-based teaching practices. By May 2020, it is projected that over 40,000 students will have taken courses that were developed in this manner.

Faculty participating in the grant completed the Teaching Practices Inventory (TPI) developed by the Wieman Institute. The inventory measures the extent to which instructors use research-based teaching practices (ETP). Faculty use of research-based teaching practices in strategic alignment with active learning and adaptive courseware provided the greatest measure of success. In general, instructors with ETP scores above 24 had higher course success rates than those with lower ETP scores. However, these differences were statistically significant for instructors of STEM courses with ETP scores of 30 and higher. Data indicates that simply adding adaptive courseware is not enough to impact student success. It is the combination of: 1) strategic implementation of courseware, 2) backward course design, and 3) the incorporation of research-based teaching practices that has the most potential to impact student success.

KEYWORDS:

adaptive courseware, research-based teaching, Teaching Practices Inventory, backward design, active learning, learning assistants

DISCIPLINES:

Educational Methods, Educational Technology, Instructional Design

A TRANSFORMATIVE APPROACH TO INCORPORATING ADAPTIVE COURSEWARE: STRATEGIC IMPLEMENTATION, BACKWARD DESIGN AND RESEARCH-BASED TEACHING PRACTICES

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Colorado State University is an R1 university located in Fort Collins, Colorado, sixty miles north of Denver. The university serves an undergraduate population of over 26,000 students. As a land-grant institution, the university's inherent mission is to serve all Colorado residents and intentionally recruit and support historically underrepresented students, including students of color, first-generation students, and low-income students.

INTRODUCTION

Student success, retention and persistence play a significant role in the current higher education landscape from both a financial and academic standpoint. More than any other time in history, institutions serve a student body diverse in educational, ethnic, and socio-economic backgrounds, prompting the need to reexamine both structural and pedagogical traditions. Colorado State University (CSU) faced the student success and retention challenge in 2007 with the first of two Student Success Initiatives that would raise retention rates for all students regardless of their background. The first Student Success Initiative (SSI 1) focused on establishing university wide structures that promoted student success and resulted in the creation of academic learning communities, dedicated academic advisors, tutoring and study groups, and the Institute for Learning and Teaching (TILT). SSI 1 achieved “historic highs in retention rates among first-year freshmen and transfer students, and historic highs in four-, five- and six-year graduation rates all while reducing graduation gaps for first generation, low-income and minority groups.”¹

In 2011 CSU's president, Dr. Tony Frank, challenged the university to increase the six-year graduation rate to 80% with *no gaps* in success for the Fall 2020 cohort. This new challenge prompted university administrators to embark on

¹ <https://source.colostate.edu/colorado-state-university-helps-launch-national-effort-to-boost-student-access-and-achievement/>

Student Success Initiative 2 (SSI 2), shifting the focus to faculty impact on student success by “[better equipping] faculty and staff with awareness, strategies, and tools that make the greatest difference in learning- and support-focused interactions.”² The initiative included Intergroup Relations training, Inclusive Pedagogy training, and the development of the Teaching Effectiveness Framework (TEF) to guide pedagogical professional development and teaching evaluations.

In July 2016, CSU joined seven other public and land-grant institutions in the *Accelerating Adoption of Adaptive Courseware* grant sponsored by the Personalized Learning Consortium (PLC) of the Association of Public and Land-grant Universities (APLU). The grant supported data collection for four academic year cohorts ending in May 2020 and required 15% - 20% of the general education enrollments be taught with an adaptive courseware component. The courseware grant was viewed as an opportunity to support SSI 2 by offering personalized learning to CSU students and individualized support to faculty. A primary objective of the grant was to further knowledge on the use of adaptive courseware in high-enrollment, general education courses.

WHAT IS ADAPTIVE COURSEWARE?

Adaptive courseware tailors’ content to students’ current levels of knowledge by assigning problems or activities appropriate to the level of mastery the student has demonstrated in answers to previous problems. The courseware collects learning analytics data and provides reports that faculty members can use to make decisions related to instructional practices, student engagement, and formative feedback. Adaptive courseware technology supports students in achieving *foundational* learning objectives outside of class, promoting mastery at the lower levels of Blooms’ Taxonomy (Gebhardt, 2018).

PURPOSE

A primary objective of the grant was to scale the adoption of adaptive courseware in general education courses at each of the grant institutions. CSU targeted high-enrollment, general education courses. As demonstrated in Table 1, CSU scaled quickly with 11,336 enrollments, just shy of the 12,300 enrollment target, within two years. By May 2020, it is projected that over 40,000 CSU students will have taken courses that were developed following the combination of backward design, adaptive courseware, and research-based teaching practices implemented as part of participation in the grant.

² <https://studentsuccess.colostate.edu/about/student-success-initiative-2/>

METHODS --- INTEGRATING ADAPTIVE COURSEWARE

Though not required by the grant, CSU took a three-pronged, transformative approach to the integration of adaptive courseware. Instead of simply adding adaptive courseware to the course, CSU divided the courseware integration into three components: 1) strategic implementation of courseware, 2) backward course design, and 3) incorporation of research-based teaching practices. Specifically, instructional designers from the Institute for Learning and Teaching (TILT) regularly consulted with faculty to determine the best adaptive courseware and research-based teaching practices that aligned with course objectives and instructional goals. CSU's additions to the grant requirements were intended to promote academic success for all students, but particularly for students from historically underserved groups, since active learning with increased structure has been shown to reduce the achievement gap (Haak et al., 2011). In 2016, 23% of CSU students were Pell-eligible and 42% were at-risk, as first-generation, low-income, and/or racially/ethnically diverse learners. In alignment with SSI 2, the goal was to eliminate the gaps for these traditionally underserved students while still benefiting all students.

Table 1

Scaling the use of adaptive courseware Fall 2016-May 2020

Academic Year	Enrollments using courseware at end of term (EOT)
2016 - 2017	3,124 in 51 sections
2017 - 2018	8,212 in 82 sections
2018 - 2019	15,175 in 125 sections
2019 – 2020	<i>Anticipate 15,200 enrollments in 126 sections</i>
Grant Total	Estimate 40,000+ enrollments through May 2020

STRATEGIC IMPLEMENTATION OF ADAPTIVE COURSEWARE

In 2016, the systematic use of adaptive courseware was still in its infancy and academic research was limited; information related to the effectiveness of adaptive courseware existed largely as publisher/vendor reports and white papers. Thus, the lack of research literature at that time was a barrier to the adoption of adaptive courseware use among faculty members who were hesitant to adopt a technology without a neutral or peer-reviewed process that attested to effectiveness of adaptive courseware. Therefore, we targeted faculty members willing to be early adopters and willing to experiment with the courseware despite the lack of peer-reviewed literature.

Recruiting courses for courseware adoption. In an effort to address the success gap for historically underserved students, the adaptive courseware grant targeted courses with:

- high enrollment numbers to impact scaling;
- high rates of D's, F's, or withdrawals (DFW) and/or high number of Pell recipients;
- courses identified by CSU Institutional Research, Planning and Effectiveness as predictors of graduation; and
- faculty members who were willing to be early adopters and incorporate an adaptive courseware platform as a graded and integral part of the student workload.

Participating faculty received the following incentives:

- a salary stipend upon signing a *Memorandum of Understanding*;
- individualized instructional design support; and
- membership in a faculty learning community.

Courseware selection. Per the adaptive courseware grant, faculty chose from twenty-one approved adaptive learning platforms as selected using the *Courseware in Context Framework (CWIC)* developed by Tyton Partners. When choosing an adaptive courseware platform, faculty members were most concerned with the textbook associated with the platform. In other words, faculty prioritized the content quality over features of the adaptive courseware. Courseware vendors used by CSU grant participants included: McGraw-Hill LearnSmart with Connect, Pearson MyLabs, Wiley-Plus Orion, MacMillan Learning Curve with LaunchPad, Inquizitive, and CogBooks.

Use of courseware analytics to support students. Overall, vendors promote the courseware analytic dashboard as a way to identify: 1) students who may be struggling and 2) the learning objectives or key concepts that may need clarification. While the specifications of these products vary, adaptive courseware provides space for students to engage with foundational course content outside the classroom (beyond reading the text). Ideally students' engagement with course content outside of class frees up class time for instructors to focus on active learning and on student processing of material at a higher-level, building on the foundational knowledge students have learned from interacting with the courseware. The courseware reports typically provide instructors with information related to student performance in the courseware and identifies content areas in which students struggle or may need additional instruction. This information can inform how the instructor may approach subsequent class sessions.

FACULTY PROFESSIONAL DEVELOPMENT

(BACKWARD) COURSE REDESIGN CONSULTATIONS

Following the principle of backward design, the redesign process started with a review of course learning outcomes (Wiggins & McTighe, 2005). Faculty members were encouraged to revise ambiguous or outdated course outcomes and use these revised outcomes to anchor course content – both within the adaptive courseware and within the lecture materials, as well as throughout classroom-based activities. This alignment of adaptive courseware, content, and activities is an important aspect of a successful implementation (Wozniak, 2016).

The instructional design team created a checklist (provided herein as Appendix A) consisting of six phases of implementation for onboarding participating faculty. The phases included: 1) Explore, 2) Strategize, 3) Formalize, 4) Design, 5) Implement, and 6) Wrap-up. The checklist allowed instructional designers to determine faculty and student needs, to track progress, and to standardize consultations for each grant participant. During the course redesign phase, instructional designers used the *Classroom Observation Protocol for Undergraduate STEM (COPUS)* to observe grant participants and determine the extent and type of support needed for individual participants (Smith, 2013). The COPUS directly aligns with the *Teaching Practices Inventory (TPI)* self-assessment discussed later in this work (Wieman, 2014).

RESEARCH-BASED TEACHING PRACTICES

During the redesign, instructional designers worked with faculty to identify one to two course concepts or units in which students would benefit from the incorporation of research-based teaching practices, including but not limited to multiple in-class formative assessments; low-stakes warm-up exams within the first four-weeks of the class; metacognitive post-exam “wrappers,” or self-reflections that encouraged students to reflect on test performance; common misconceptions and student errors explicitly shared with students; and active learning. In a limited number of cases, peer educators known as Learning Assistants (LAs) were added to facilitate small group learning during class, allowing the scaling up of collaborative and active learning in high enrollment courses. The combination of adaptive courseware to prepare students, the instructor’s use of research-based teaching practices, and the integration of LAs to help guide and engage students in challenging and collaborative learning activities during class can be another transformative approach to teaching (Talbot et al., 2015).

FACULTY LEARNING COMMUNITY

Grant participants were invited to participate in the Faculty Collaboration Group, a grant-specific faculty learning community that typically met for ninety-minutes five times throughout the academic year. The faculty learning community provided instructional designers a forum to share just-in-time professional development grounded in research-based teaching practices through mini-workshops and modeling. The meetings also fostered cross-discipline collaboration and provided faculty an opportunity to share teaching successes and challenges related to adaptive courseware and in-class teaching practices.

Cross-discipline collaboration. The cross-discipline nature of the faculty learning community allowed faculty to learn with and from peers with whom they did not typically engage. For example, discipline-based teams (biology, chemistry and accounting) whose members worked together to redesign their courses would branch out and work with faculty from physics, philosophy, economics, and history during the Faculty Collaboration meetings. Also, faculty from psychology often started the meeting with an activity focused on the science of learning and its teaching application relevant to all disciplines.

Adaptive courseware and the teaching effectiveness framework. The Teaching Effectiveness Framework (TEF) developed at CSU consists of seven domains of teaching effectiveness and is used to guide faculty and departments in developing and evaluating teaching. The domains include: Curriculum/Curricular Alignment, Classroom Climate, Pedagogical Content Knowledge, Student Motivation, Inclusive Pedagogy, Feedback and Assessment, and Instructional Strategies. Many of the teaching strategies presented during the Faculty Collaboration meetings focused on the Feedback and Assessment domain of the Framework. The metacognitive and self-regulated learning features found in adaptive courseware align with learning theory and teaching practices related to Feedback and Assessment. During Faculty Collaboration meetings, instructional designers modeled in-class feedback strategies, such as creating and comparing concept maps in small groups or writing iClicker questions to review the concepts student most struggled with in the previous week's courseware assignment.

Instructional designers also guided the faculty learning community in a goal setting process to develop community members' teaching using the TEF. During a faculty collaboration meeting, faculty members were encouraged to choose one domain and set a teaching goal; faculty teaching goals were used to inform topics for future Faculty Collaboration meetings.

Dashboard challenge. Analytic dashboard reports in adaptive courseware are designed to provide learning analytic data to faculty to allow faculty members to:

- 1) make instructional decisions related to concepts that may need further discussion,
- 2) determine which students are struggling and would benefit from instructor outreach, and
- 3) increase the faculty use of formative feedback through the adaptive courseware system.

The various adaptive courseware platforms adopted at CSU use student data and interactions to populate sophisticated analytics dashboards. Instructors can use these reports to make data-driven decisions about class activities and assignments focusing on student needs. However, the power of the learning analytics cannot be fully applied without faculty engaging with the data nor without faculty members implementing interventions that address gaps in student learning (Cai, 2018). Upon the realization that the analytic dashboards were rarely used, faculty were invited to partake in the *Dashboard Challenge*. During the challenge, each participant recorded in a Google spreadsheet time spent using the dashboards, data collected, the intervention initiated, and the results achieved. At the completion of the challenge the faculty participants received one of three books addressing research-based active learning strategies.

The faculty response to the Dashboard Challenge was varied during its two-semester implementation. While faculty committed to using one key report from the analytic dashboard in fourteen different course sections, only six sections were still recording usage of the dashboard at the end of the eight-week period. Overall, faculty feedback related to the analytic dashboard was mixed. The Chemistry faculty had prior experience using ALEKS and reported that the dashboard provided helpful information that was used to make instructional decisions. However, faculty using a platform new to them had difficulty with each of the following:

- allocating time to run reports,
- selecting which report would provide valuable data,
- fully understanding the data presented which led to trust issues with the accuracy of the data.

Curated professional development opportunities. Members of the faculty learning community also took advantage of additional professional development opportunities, both as participants and presenters. The following professional development opportunities were designed with grant participants in mind and offered on campus:

CSU Summer Conference 2017. Dale Johnson, from Arizona State University (ASU) shared the use of adaptive courseware at ASU.

CSU Summer Conference 2018. Dr. Ben Wiggins, from the University of Washington, presented on active learning in large classrooms and held a special two-hour session for the grant recipients. Also, three grant recipients shared their experiences using adaptive courseware and research-based teaching strategies.

CSU Summer Conference 2019. Dr. Sarah Eddy, from Florida International University, presented research findings on the benefits of active learning. Also, three grant recipients presented on adaptive courseware, active learning and classroom climate.

RESULTS

In an effort to demonstrate the impact of the use of adaptive courseware in conjunction with research-based teaching practices, CSU collected the following evidence:

1. Student success data
2. Faculty survey data regarding use/implementation of the courseware
3. Teaching Practices Inventory data

MEASURING THE USE OF RESEARCH-BASED TEACHING PRACTICES

Faculty participating in the grant completed the *Teaching Practices Inventory* (TPI). The TPI is a faculty self-assessment tool which extracts a numerical score that reflects the *extent to which instructors use research-based teaching practices*. The score of the Extent of use of Teaching Practices (ETP) ranges from 0 – 67 and is based on the self-reported use of practices that improve student learning (Wieman, 2014). For example, providing a list of topics to be covered in the course is worth one point, while providing a list of topic-specific competencies students should achieve is worth three points. In general, the ETP scores in this report represent the use of research-based teaching practices for the course as a whole after the course had been redesigned to include adaptive courseware.

Faculty surveys and ETP data from the Teaching Practices Inventory were collected anonymously by TILT instructional designers using Qualtrics, a web-based survey and data collection tool. The instructional designers provided staff members of Institutional Research, Planning and Effectiveness information regarding the sections and instructors participating in the adaptive courseware grant. A total of 254 sections in 28 unique courses utilized adaptive courseware combined with active learning between fall 2016 and spring 2019. Over fifteen-thousand students participated in at least one adaptive/active course section during this period.

POPULATION

As shown in Table 2, below, students included in this study were enrolled in a course that utilized an adaptive courseware platform/active learning. Demographically, students are similar by adaptive/active courseware status. This is not surprising since enrollment in these sections is somewhat random and adaptive courseware was not advertised in the catalog as a component of any section of any course. Counts do not represent unique students as some students may have taken more than one adaptive course, or an adaptive/active section of one course and a non-adaptive section of another course.

Table 2

Student Demographics by Adaptive/Active and Non-Adaptive Course Enrollment

	Non-adaptive	Adaptive/Active	Overall
Headcount	13,780	13,858	26,960
Female	58.0%	57.8%	57.9%
CCHE index ³	114.0	114.4	114.2
First generation	25.2%	25.5%	25.4%
Pell recipient	21.6%	21.7%	21.6%
Racially minoritized	24.1%	26.6%	25.4%

³ The Colorado Commission on Higher Education (CCHE) index is a quantitative measure of a student's academic preparation that utilizes the student's high school GPA or high score rank percentage combined with ACT or SAT score. The use of the index in admission was retired starting in Fall 2019. Source: <https://higher.ed.colorado.gov/Academics/Admissions/IndexScore/Default.asp>

COURSE LEVEL SUCCESS BY ADAPTIVE COURSEWARE/ACTIVE LEARNING STATUS

Student success outcomes pre- and post-redesign provided evidence for the effectiveness of the adaptive learning platform with the inclusion of active learning. Student and faculty surveys designed and administered by instructional designers provided insight into these users' experiences with the adaptive technology, and explored topics related to ease of use, perceived impact on grades, and effectiveness in the classroom.

Table 3 displays the course success rates for each course and instructor by adaptive courseware/active learning use. Comparisons are made at the instructor level to control for individual pedagogical differences. Bold text indicates instances in which the success rates for adaptive/active sections are at least 1 percentage point (PP) higher than the non-adaptive sections; italicized text indicates instances when adaptive/active sections are at least 1 PP lower than the non-adaptive sections. Additionally, Table 3 displays the Pearson Chi-square p-value for each course/instructor pair; success rates with statistically significant differences (p-value $\leq .05$) are marked with an asterisk (*).

The effect of adaptive courseware/active learning on student success should be evaluated on a case-by-case basis. For example, for ECON204 the 86.8% success rate for students in the adaptive/active group is significantly higher than the 78.1% success rate for non-adaptive group. While LIFE102 (with Instructor X941) shows similar success rates for adaptive/active and non-adaptive sections (85.5% versus 79.7%), these rates are statistically similar (p-value $> .05$). Despite the lack of statistical significance, the difference may warrant some practical significance: the 5.8 percentage point higher success rate in the adaptive/active sections equates to an additional 17 students passing the course compared to the non-adaptive sections.

DATA ANALYSIS OF TPI SCORES RELATED TO SUCCESS RATE

Extent of the use of Teaching Practices scores were obtained for 21 faculty members participating in the grant. Table 4 displays the course success rates by ETP score range. Bold text indicates instances in which the success rates for adaptive/active sections are at least 1 percentage point higher than rates for the non-adaptive sections; italicized text indicates instances in which adaptive/active sections are at least 1 percentage point lower than the non-adaptive sections. Additionally, the Pearson Chi-square p-value for each ETP score range is displayed; success rates with statistically significant differences (p-value $\leq .05$) are marked with an asterisk (*). In general, instructors with ETP scores above 24 had higher course success rates than those with lower ETP scores. However, these differences were statistically significant only for instructors of STEM courses with ETP scores of 30 and higher.

Table 3*Adaptive/active and Non-adaptive Student Success Outcomes by Course and Instructor*

Course & Instructor		Headcount		A, B, C, or S grade		PP difference	Pearson Chi-square
		Non-adaptive	Adaptive /Active	Non-adaptive	Adaptive/Active		
BZ 101	Z911	714	664	71.0%*	76.8%*	5.8	0.01
BZ 110	Z911	1,028	1,074	70.1%	72.3%	2.2	0.26
CHEM 111	Q259	255	428	64.3%*	82.0%*	17.7	<0.01
	E610	572	445	78.5%	78.7%	0.2	0.95
CHEM 113	I274	511	503	77.5%	78.7%	1.2	0.64
ECON 202	D163	661	523	86.5%	85.3%	-1.3	0.54
ECON 204	D849	265	280	78.1%*	86.8%*	8.7	0.01
FSHN 150	B566	142	305	90.8%	91.1%	0.3	0.92
	X228	372	165	68.3%	69.7%	1.4	0.74
	K908	353	362	88.1%	87.0%	-1.1	0.66
HES 145	G490	184	151	93.5%	87.4%	-6.1	0.06
HIST 150	I786	108	79	86.1%	92.4%	6.3	0.18
HIST 151	Q672	105	102	85.7%	84.3%	-1.4	0.78
LIFE 102	W394	748	749	77.8%*	82.0%*	4.2	0.04
	L298	610	303	75.1%	74.9%	-0.2	0.96
	R419	330	299	67.3%*	79.6%*	12.3	<0.01
	X941	305	303	79.7%	85.5%	5.8	0.06
LIFE 103	W394	275	271	88.7%	90.0%	1.3	0.62
	R214	227	235	70.5%	74.0%	3.6	0.39
PH 121	J78	989	990	95.1%	94.9%	-0.2	0.84
	C717	318	341	94.7%*	90.6%*	-4.0	0.05
PH 122	J78	862	1,228	97.9%	97.1%	-0.8	0.28
PHIL 100	H282	305	273	76.7%*	85.3%*	8.6	0.01
PSY 100	P173	306	690	80.1%	79.4%	-0.6	0.82
	H366	177	142	87.0%	86.6%	-0.4	0.92
	L822	319	658	85.9%	82.2%	-3.7	0.15
	O203	332	664	79.2%*	88.9%*	9.6	<0.01
	S354	350	164	87.4%	90.2%	2.8	0.35

* Statistically significantly different at $p \leq .05$

FACULTY REPORTED RESULTS

Some faculty collected their own data related to the addition of adaptive courseware and research-based teaching practices. Faculty from economics and physics were already using adaptive courseware prior to their participation in the grant. However, before the grant they used the courseware *only as an optional study tool* and *not* as a graded, integral part of the content delivery. As grant participants, faculty in economics and physics agreed to incorporate the courseware as a graded assignment. Instructional designers partnered with these early adopter faculty members to kick-start faculty recruitment and share the success of the economics and physics courses early in the grant.

Table 4

Adaptive and Non-adaptive Student Success Outcomes by Course Type and ETP Level

Course type and ETP score		Headcount		A, B, C, or S grade		Percentage points difference	Pearson Chi-square
		Non-adaptive	Adaptive /Active	Non-adaptive	Adaptive/Active		
STEM	49-37	4,676	4,904	82.5%*	85.0%*	2.4	<0.01
	34-30	865	731	71.9%*	79.1%*	7.2	<0.01
	27-24	1,207	1,171	82.7%	84.5%	1.9	0.22
	21-18	353	362	88.1%	87.0%	-1.1	0.66
Non-STEM	34-30	759	1,401	83.0%	85.9%	2.9	0.07
	27-24	611	963	78.4%	81.1%	2.7	0.19

* Statistically significantly different at $p \leq .05$

Economics. Introductory courses in economics were redesigned by a team of graduate student instructors led by the course coordinator and supported by instructional designers. One course section also incorporated Learning Assistants. The course coordinator reported the following results, attributing these results to the collaborative nature of the course redesign process:

- *Improved Teaching.* Due to the team approach, instructors only had to focus on designing several weeks' worth of course content. This resulted in very high-quality content and allowed more time for instructors to improve in-class presentations, work with students, and respond to emails.
- *Level Playing Field.* Students, regardless of instructor, were treated consistently.
- *Consistent Course Grade Outcomes.* Course grades across all course sections and instructors were not statistically significantly different.

Physics. The lead physics instructor identified the following outcomes following the addition of courseware as a graded component and Learning Assistants in his courses with over 220 students:

- *Improved Qualitative and Quantitative Reasoning.* On qualitative questions on reading quizzes, the fraction of students getting scores of less than 50% decreased by one-third. On quantitative exam questions, students provided answers that better aligned with the laws of physics.
- *Improved Exam Performance.* Students demonstrated distinct improvements in exam scores on tests of similar difficulty; the instructor was able to increase rigor without reducing scores.
- *Greater Student Success.* The already low DFW rate was reduced further, and the number of students with truly low scores noticeably decreased.

FEEDBACK FROM FACULTY MEMBERS REGARDING ADAPTIVE COURSEWARE

While feedback from faculty members has been mixed, most feedback has been positive. In follow-up conversations, surveys, and focus groups conducted by instructional designers, faculty members provided the following advice to their colleagues:

- *Be sure to give yourself plenty of time, and get support in place, as you implement the adaptive courseware.*
- *Get training on how to use the reports and learn how to integrate the reports into your teaching.*
- *Really consider and think through the purpose (adaptive learning) will serve and the role it will fill in your class and in the students' learning. Do it intentionally, rather than for checking a box, because this will yield better outcomes. Make sure the connection to other course content is clear, otherwise it may lead students in the wrong direction.*
- *Do It! Adaptive courseware is great for visual learners and also allows more time in class for active teaching, discussions, and targeted topical activities to solidify a concept.*
- *The courseware is excellent for preparing students for lecture and as an additional resource for understanding the material.*
- *Use the metrics to help define which parts of the content are not being comprehended as a trend.*
- *(Adaptive courseware is) a valuable tool, but it is not a magic bullet.*

- *Choose a textbook system that you are comfortable with. Check with others to make sure you know the pros and cons of that system before adopting.*
- *Make (adaptive courseware) graded but a minimal portion of the overall grade. Most students who attempt the assignments earn full credit and it is not a reflection of their true understanding of the material.*
- *... it is a great experience and an awesome way to keep students engaged and motivated in the class. Also, the adaptive courseware allows for other types of questions and self-graded assignments that might assist instructors in large sections.*
- *Adaptive courseware has encouraged students to engage more with reading material and independent study skills... Using adaptive courseware has taken the pressure off me to lecture on everything in the text, giving me more time to use discussions and other active teaching/learning strategies in class.*

Further, faculty had the following recommendations for vendors:

- *The adaptive courseware questions did *not* always correspond well with what I covered in lecture or even what the questions should have corresponded to in the section of the textbook. This was frustrating for students and for me. I actually did the homework also and was often surprised by aberrations in the kinds of questions asked and in the level of detail they went into. I think this, aside from making students frustrated and eroding their confidence in the platform, means that I cannot accurately assess the impact of the courseware on student performance or engagement.*
- *Make it more applicable to what I am teaching. There is very little control in the current version that allows the questions associated with the reading to reflect the things that I would REALLY like them to understand before coming to class. Many of the students would think that because the courseware focused extensively on one thing that they struggled with (even if I indicated that that particular subsection of the text should not be included) that would be what they would be assessed on for the exam, when, in fact, it wasn't even something that I thought was important enough to cover in class. It would also be helpful to see the range of questions that my students were asked. That way, if a student was directed down an irrelevant rabbit hole, I could reach out and try to fix that.*
- *Better integration with the Canvas gradebook (sometimes grades don't automatically transfer from Connect to Canvas).*

DISCUSSION

In general, instructors involved in the grant believed the platforms helped their students become more engaged in course material, and there tends to be a slight positive association between the adoption of adaptive courseware with active learning and the course success rate. The use of adaptive courseware with active learning appears to be generally favorable and not detrimental to student success. Faculty use of research-based teaching practices in strategic alignment with active learning and adaptive courseware provided the greatest measure of success.

The challenge for faculty is to implement the adaptive courseware in a way that is manageable (to *both* the instructor and students) and beneficial for students. Moreover, adaptive platforms need to give faculty the ability to select the specific questions and courseware content to avoid presenting information that is irrelevant and does not align with course objectives. When assessing the value of adaptive courseware to the university community, special consideration should be paid to:

- 1) the courseware's impact on the depth of student learning,
- 2) student achievement of learning objectives, and
- 3) how the faculty member uses the data from the analytic dashboard to inform instruction.

In sum, these aspects of adaptive courseware cannot be measured simply through comparisons of course success rates. Rather, the institutions need to assess the true value of adaptive courseware through a variety of techniques involving analysis of data collected from those using the technologies who have reported directly on the aspects that enhanced or had a positive impact on their experiences as learners and teachers.

LIMITATIONS

Overall, standardizing course redesigns, adaptive courseware adoption, and active learning practices were challenges. In an effort to best meet the needs of faculty, course content and students, redesigns were tailored to each course's needs and each instructor's teaching styles. Faculty members' levels of comfort with implementing research-based teaching practices varied as well. Each redesign required customization to utilize best each instructor's unique skill set.

All courses were redesigned to accommodate the addition of adaptive courseware chosen from one of the twenty-one approved vendors. The approved courseware options offered an array of features and reporting capabilities. In some instances, faculty found the reporting dashboards and analytics of some platforms to be too rudimentary to be useful, while other platforms' complexity (user interface and reporting) proved to be a deterrent to their use. Reporting terminology and

definitions also varied and were unique to each platform. This made comparing data across multiple platforms too difficult and imprecise to be useful.

Further, variation in teaching load between semesters (cycling in and out of teaching specific courses) had the potential to influence courseware adoption and use, and the potential to influence research-based teaching practices. This variation in teaching schedules is reflected in the sections selected for the analyses included in this report. Ideally, comparisons between adaptive and non-adaptive sections are made between like terms (fall-to-fall or spring-to-spring), yet in some instances fall-to-spring comparisons were made.

While the Extent of use of Teaching Practices (ETP) score from the Teaching Practices Inventory (TPI) provides an indication of a faculty member's use of a teaching practice (e.g., collaboration or sharing in teaching, providing supporting materials, feedback and testing), the ETP score does not assess the quality of implementation of teaching practices. Additionally, the TPI was developed in two versions, one to assess ETP in STEM courses and another for Humanities courses. Since the two versions are similar and the majority of courses participating were STEM, the STEM version was used across all CSU courses, for the sake of consistency. Lastly, while over 40 instructors participated in the grant, ETP scores were obtained for only about half of them, thus the comparisons represent a subsample of the redesigned courses.

LESSONS LEARNED

ADAPTIVE PLATFORM ADOPTION AND USE

Taking a transformative approach to the implementation of adaptive courseware was a high-touch, time-intensive endeavor. Faculty had competing priorities. Moreover, the simultaneous processes of incorporating research-based teaching practices *and* adaptive courseware - technology, student communication, and analytic data inventions - required a multi-pronged approach, including each of the following resources:

- 1) committed support from upper administration;
- 2) a deep, explicitly identified connection between the new effort and an ongoing university initiative;
- 3) access to instructional designers;
- 4) formation of and/or participation in a faculty learning community;
- 5) relevant professional development opportunities;
- 6) participation stipends;
- 7) a forum to recognize faculty members' participation in the grant.

To help ease the changes and transitions, future redesigns should place a stronger emphasis on the use of data from the analytics dashboards as an integral part of the redesign earlier, during the design process. Lessons learned include:

Content quality is key to faculty adoption. When selecting adaptive courseware, faculty are most concerned about content quality, as opposed to courseware functionality. If the content is not of high-quality, then faculty members will choose a different textbook or courseware platform.

Adaptive courseware must be easy to use – for faculty and students. Adaptive courseware needs to be intuitive and easy to access since faculty members have little time to provide technical support to students.

Require faculty to commit to using one analytic report at the onset. The institution should place a strong emphasis on the use of one or two key reports from the analytic dashboard to ensure regular use of the analytic dashboard for the purpose of making instructional decisions.

Encourage vendors to incorporate automated analytics reporting. Faculty members have expressed a preference for automated analytics reporting; special consideration may be given to a platform with such capabilities and course redesigns can incorporate the interpretation of these features.

FACULTY RECRUITMENT AND PREPARATION

Gaining faculty buy-in when adopting new educational technologies or new instructional strategies is key to the success of the implementation. A few key lessons related to preparing faculty members for taking on an initiative include:

Solicit administrative support. The adaptive courseware implementation at CSU benefited from the support of the president and provost. The scaling of innovative teaching and learning practices requires support, resources and incentives from university leadership (Hall et al., 2016).

Identify faculty champions. Recruit faculty members who tend to be early adopters and who are willing to share their story across campus. Faculty members are interested in hearing from colleagues within their own discipline. In addition, faculty members who teach large-enrollment classes are particularly interested in learning from and observing colleagues who also teach large classes.

Reinforce the alignment of content with course outcomes. Faculty members need to be willing to trim excess content from class time so they can focus on the outcomes. This applies to content delivered via the adaptive courseware as well as content delivered during class time. Students expressed frustration when courseware content did not align with course outcomes.

Manage time expectations. It takes substantial course design time to ensure alignment between course outcomes, content, research-based teaching practices, assessments, and the adaptive courseware.

RECOMMENDATIONS FOR FUTURE RESEARCH

LONG-TERM IMPACT OF COURSEWARE USE ON SUBSEQUENT COURSES

While this paper discusses the impact of redesign and the use of adaptive courseware on individual courses, more longitudinal research is needed on the long-term effects on learning and retention for students who experienced adaptive courseware and active learning in high-enrollment general education courses. Does the use of adaptive courseware aid in the retention of core concepts and subsequently provide a firmer foundation of knowledge for future coursework?

EFFECTIVE USE OF LEARNING ANALYTICS

To compare the effectiveness of adaptive courseware, vendors must be willing to agree to a common baseline set of data, reports, and learning analytics. This common dataset would be IEEE Caliper compliant, enabling institutions to gather aggregated learning analytics from all courseware platforms.

LESSONS LEARNED FOR FUTURE DATA COLLECTION

Link student and faculty surveys. The student and faculty surveys were anonymous and independently programmed. Embedding the section identification or course reference number as part of the surveys and datasets would enable direct comparison of student data within each instructor's course. For example, such logging of data would facilitate:

- tracking the classroom culture and teaching practices related to the use of adaptive courseware;
- addressing the “helpfulness” of courseware from the student perspective by tracking if the courseware is simply an additional tool or is tightly integrated into teaching practices; and
- comparing the instructors' ratings of the use of active learning in the classroom with students' ratings of their anticipated course grade.

Link adaptive courseware to courses. Up to seven different adaptive courseware platforms were utilized for this grant and it is unclear which platforms were used for which courses, whether instructors utilized more than one platform across their course(s), or how many different platforms a student may have used (since some students enrolled in multiple courses that utilized adaptive courseware during the grant period). Linking student success, as well as student and faculty

perceptions and preferences, to each platform could reveal whether there is a better/best or preferred platform that could be adopted on a larger scale for the university overall. Additionally, students reported that the connection between the courseware content and classroom content is not always evident. Further investigation is warranted to determine if such connections are related to the level of customization for a particular platform, timing of content delivery, or other issues.

In-depth student and faculty assessments. Focus groups or interviews with students and faculty could provide insight into how these stakeholders utilized adaptive courseware but also, and more importantly, how utilization impacted the classroom and learning environments.

Analyze faculty strengths as indicated by the Extent of the use of Teaching Practices (ETP) sub-category scores in relation to student success rate. Aligning ETP sub-category scores such as “in-class features and activities,” “assignments,” or “supporting materials provided” with student success rate could provide insight into which specific practices positively affect student achievement.

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APPENDIX A: IMPLEMENTATION CHECKLIST

Adaptive Courseware Grant - Implementation Checklist

Course Information:

Number and Title	
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Contact Information:

	Name	Email	Phone
Project Lead			
Faculty			
TILT			

Phase	Activity	Who & When
Explore	<ul style="list-style-type: none"> ○ Discuss <i>Grant Summary</i> document ○ Review <i>Memo of Understanding (MOU)</i>, especially departmental & participant expectations ○ Review adaptive platform options ○ Discuss project timeline ○ Review course syllabus and objectives to target opportunities for redesign ○ 	
Strategize	<ul style="list-style-type: none"> ○ Discuss recruitment meeting ○ Determine ID's and roles for project ○ 	
Formalize	<ul style="list-style-type: none"> ○ Discuss course outcomes and syllabus ○ Choose adaptive courseware platform ○ Determine formal Project Plan and Milestones <ul style="list-style-type: none"> ○ Classroom observation(s) ○ Future meetings ○ Progress reports ○ Discuss grant assessment/research: <ul style="list-style-type: none"> ○ APLU IR data requirements ○ Options regarding student engagement, learning and/or academic achievement data ○ Course observations, etc. ○ Discuss <i>Teaching Practices Inventory</i> ○ 	
Design	<ul style="list-style-type: none"> ○ Collect signed MOU ○ Determine design needs (syllabus, objectives, technology, HIPs, course map, etc.) ○ Plan adaptive courseware technology integration (platform set-up, use & vendor support) ○ Discuss campus partnerships if applicable ○ Complete pre-redesign <i>Teaching Practices Inventory</i> ○ Identify and schedule grant assessment/research ○ Develop student communication plan (technology & HIPs) ○ Determine and plan high-impact practices ○ 	

Implement	<ul style="list-style-type: none"> ○ Use adaptive platform ○ Incorporate high-impact practices ○ Adhere to grant assessment/research plan ○ Complete status reports as scheduled ○ Observe course on a designated HIP day ○ Adjust platform & HIP integration as needed ○ 	
Wrap-up	<ul style="list-style-type: none"> ○ Complete post-redesign <i>Teaching Practices Inventory</i> ○ Determine lessons learned (plus/delta, etc.) ○ Schedule future updates and/or revisions as needed ○ Write a project summary ○ 	

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Adaptive Analytics: It's About Time

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ADAPTIVE ANALYTICS: IT'S ABOUT TIME

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ABSTRACT:

This article describes a cooperative research partnership among a large public university, a for-profit private institution and their common adaptive learning platform provider. The focus of this work explored adaptive analytics that uses data the investigators describe as metaphorical “digital learning dust” produced by the platform as a matter of course. The information configured itself into acquired knowledge, growth, baseline status and engagement. Two complimentary models evolved. The first, in the public university, captured end-of-course data for predicting success. The second approach, in the private university, formed the basis of a dynamic real-time data analytic algorithm. In both cases the variables that best predicted students at risk (effective use of time and revision attempts) were deemed teachable skills that can improve with intervention.

KEYWORDS:

Adaptive Learning, Predictive Analytics, Higher Education, Cooperative Research

DISCIPLINES:

Research Methods, Educational Technology, Instructional Design

ADAPTIVE ANALYTICS: IT'S ABOUT TIME

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INTRODUCTION

The United States offers post-secondary learning opportunities that rival or surpass those of any other country in the world. The educational landscape offers affordances such as vocational-technical training, community college, public and private colleges and universities, for profit institutions and a host of other higher education opportunities. Truly motivated high school graduates in this country have many options to obtain a skill, certificate or degree despite the opportunity costs involved. Furthermore, higher education institutions are making extensive efforts to ensure college success. Some of these initiatives include: time-shortened degree programs, dual enrollment, experiential course credit, flexible attendance policies, credit for military training, learn while you work, and many other adaptations that remove or minimize the “you must be on campus full time” requirement.

Perhaps the most innovative transformation belongs to the online learning environment which continually develops new formats such as: fully online, blended, flipped, MOOCs and adaptive learning. These initiatives respond to the complex lifestyles of students who must manage increasing ambiguity, ambivalence, economic demands and uncertainty placed on them by our technology-mediated society. Much of this innovation appears to be motivated by our increasing understanding of the value-add that comes from certificate or degree attainment supporting a healthier society and reducing economic inequality. By building human capital we reduce crime rates, stabilize family structures, produce more civic minded citizens, and raise those living in poverty into the middle class (Becker, 2009). Depending on the discipline in which a student earns a college degree, the degree can be worth an average of one million dollars in additional lifetime income over a high school diploma; graduate degrees are worth an additional million dollars (Carnevale, Cheah, & Rose, 2011).

Despite these innovations, the educational system in the United States faces many challenges that mitigate much of what we hope to accomplish. For instance, students living in the bottom economic quartile in this country -- those anyway who do not receive additional support -- have an approximate 10% chance of obtaining

a college degree; the odds against them are 9:1: however, students living in the top economic quartile in this country are 90% sure of college graduation; their odds of success are 9:1 (Sherman, 2015). These data regarding an unacceptable inequality, sometimes referred to as the Mathew effect (Saleh, & Sanders, 2014), confirm the *prosperity advantage* in our educational system. The economics of attending college compound the impacts of disproportionate opportunity. Burgeoning loans are crippling students with long term pay back responsibility. Unfortunately, those living in poverty who can least afford this kind of financial support have to borrow the most (Mitchell & Hackman, 2019). This creates the scarcity phenomenon described by Mullainathan and Shafir (2013) in which students living in poverty are overwhelmed by the many circumstances they have to juggle in their lives. They may be holding down two part-time jobs such that full course loads are not possible. Health care becomes a significant financial problem in addition to the costs of tuition, textbooks, transportation, and additional expenses. Most often these students are forced to borrow money because, unfortunately, they simply do not get the information about how to apply for scholarships. The demands and stresses in their lives create a fragile balancing act. If a student fails in the attempt to respond to any one of these scarcity demands and stresses, that student's whole life structure can come tumbling down. Mullainathan and Shafir (2013) describe it this way:

What happens when, loaded and depleted, a client misses a class? What happens when her mind wanders in class? The next class becomes a lot harder. Miss one or two more classes and dropping out becomes the natural outcome, perhaps even the best option, as she really no longer understands much of what is being discussed in the class. A rigid curriculum – each class building on the previous - is not a forgiving setting for students whose bandwidth is overloaded. Miss a class here and there and our student has started a slide from which she is unlikely to recover. (p. 170)

Linear classes that must not be missed can work well for the full-time student; they do not make sense for the juggling poor. (p. 171)

However, scarcity appears in circumstances other than underserved neighborhoods. Consider working adults who feel pressures from their employers to obtain additional skills and academic credentials in order to progress or receive promotions. In contemporary society it is not feasible for them to take a hiatus from their work and go back to school, full time. Most face arduous time demands in the workplace, often compounded with travel requirements that, in many cases, interfere with family obligations. These working professionals have no flexibility in their lives so even taking courses online over a 16-week semester is simply not feasible. They need a compressed educational agenda. For these individuals, time is a scarce commodity.

Higher education is not immune to scarcity. For instance, faculty and administrators must cope with time demands that come from burgeoning requirements for communication, interaction, research, publication, community service, teaching, and many other aspects of the academic life. Therefore, most academics do what Mullainathan and Shafir (2013) label tunneling. They exclude other demands and concentrate on the thing that must be completed immediately, abandoning all other responsibilities. As Brene' Brown (2012) found, exhaustion is becoming a status symbol in our society.

There is an additional problem in higher education that prevents capable students from obtaining a degree. Anthony Jack (2019) in his book *The Privileged Poor* documents how doubly disadvantaged students (those who have not received scholarships to preparatory schools primarily serving the wealthy) face a culture that unknowingly and unintentionally excludes them from the opportunities of higher education. His research shows that elite schools especially, although making every effort to give students from underrepresented neighborhoods access, force them into a culture that denies them inclusion. The Mathew effect tells these students that they don't really have a place in what Jack calls "Renowned College." Wealthy students operate with a sense of agency and empowerment. Poor students feel isolated, alone, disenfranchised and frustrated; experiences that greatly diminish their chances of success. In many instances a wonderful opportunity is lost.

THE STUDY

Given these simultaneous opportunities and challenges in American higher education, two innovations offer promise: adaptive learning and learning analytics. In this study we investigate their interaction for helping students succeed in college Algebra, a course that continues to be a challenge for students. We investigate the interaction of adaptive learning and learning analytics at two contextually different institutions whose members have worked in partnership with the research unit of their common adaptive learning platform partner, Realizeit: the University of Central Florida, a large metropolitan institution and Colorado Technical University, a primarily online for-profit institution. The cooperative partnership closely resembles the model proposed by Feldstein's Empirical Educator initiative in which universities and technology providers contribute intellectual resources to identify and evaluate effective practices in education (Feldstein, 2018). Exploring our own partnership in this work, we address the question of whether or not adaptive learning, with its variable time learning framework, provides a platform for finding actionable analytics variables that predict student success in Algebra and that also are responsive to instruction. The phrase "responsive to instruction" refers to our hope that, if we were able to identify actionable analytics variables that correlate with positive learning outcomes, we also would be able to identify possibilities for teaching curriculum designers and instructors how to manipulate these analytics variables to engineer student success.

ADAPTIVE LEARNING AND LEARNING ANALYTICS

ADAPTIVE LEARNING

Throughout the past several years, the implementation of adaptive learning has developed rapidly. However, in spite of significant funding by several national organizations (Bill & Melinda Gates Foundation, 2014; Association of Public & Land-Grant Universities, 2016; Online Learning Consortium, 2016), research results have been mixed with a 2016 meta-analysis (Yarnell, Means & Wetzel, 2016) finding only limited improvement in outcomes at 4 of 15 institutions that received funding from the Bill & Melinda Gates Foundation. Much of this research is institution centric, focusing on such things as student experience and perception of adaptive technology, its integration with mobile learning, or the efficacy of using these tools within an online or flipped classroom.

Nakic, Granic & Glavinic (2015) argued that adaptive learning can facilitate improvements in student retention, satisfaction, and the achievement of student outcomes. Dziuban, Moskal, Johnson and Evans (2016) found positive reactions to adaptive learning technology among students from two different student populations, traditional 18-22 year old students attending the University of Central Florida and adult students with an average age between 30–39 attending Colorado Technical University. Students reported that adaptive learning personalized their instruction, helping them learn the material better and increasing their levels of engagement (Dziuban, Moskal, Cassisi & Fawcett, 2016). Additionally, adaptive learning allowed the student and the faculty members to shift time to learning areas that may not get addressed in a traditional classroom setting (Dziuban, Moskal & Hartman, 2016).

Johnson and Zone (2018) and Cavanagh, Chen, Lahcen and Paradiso, (2020) discussed the importance of faculty engagement and training as fundamental to the utilization and scaling of adaptive learning technology to support data-driven decisions. Development challenges included what faculty perceived as the daunting number of components, patterns and sequences required to adapt course content meaningfully (Panicker, Kumar, Joohn & Srinivasam, 2018). Adaptive learning design can vary based upon content. For instance, courses with a linear structure, characterized by having one concept following sequentially after another with little hierarchical structure are easier to adapt (Cai, 2018).

LEARNING ANALYTICS

With today's advanced modeling and computing expertise, many universities are investigating learning analytics in an attempt to solve the higher education challenge of improving student success and retention. As students' progress through the college experience, models are formed using analytics to "predict" which students might be at risk. In fact, "technologies for improving analysis of student data" was listed as one of the top 10 strategic technologies in the 2019 EDUCAUSE Horizon Report as were "learning analytics for student success (institutional level)," highlighting the influence of these approaches today (Alexander et al., 2019).

The examination of the learning analytics national landscape conducted by Association for Institutional Research (AIR), NASPA-Student Affairs Administrators in Higher Education, and EDUCAUSE found that 91% of institutions are investing in analytic studies that are primarily descriptive. These efforts focus on describing the student environment and identifying high risk courses, although 89% of institutions were engaged in some predictive studies that examined factors influencing retention, persistence, and student GPA. Larger institutions are more likely to engage in such research. Such institutions use data-informed models to create early alerts, primarily for academic and faculty advisors (Parnell, Jones, Wesaw, & Brooks, 2018). Initiatives such as the Bill & Melinda Gates funded and EDUCAUSE led *Integrated Planning and Advising for Student Success (iPASS)* developed guidance and roadmaps for institutions by providing financial, technical, and change-management support to these colleges and universities ("Integrated Planning and Advising," 2013).

Much of the research in learning analytics has focused on work utilizing big data methods to help identify effective models that have a high degree of accuracy for predicting those students who are most likely to be at risk for not completing college (Moskal, Cavanagh, Wang & Zhu, 2020; Simanca, González Crespo, Rodríguez-Baena & Burgos, 2019; Smith, Lange & Huston, 2012; Wladis, Hachey & Conway, 2014; Miguéis, Freitas, Garcia & Silva, 2018). Algorithms have varied widely based on educational context, data at hand, and analyses used, but most have incorporated university data captured and stored in the student information system (SIS), forming the topics of conferences and journals devoted to learning analytics (Society for Learning Analytics Research, 2020; Moskal, Cavanagh, Wang & Zhu, 2020; Journal of Learning Analytics, 2020).

This learning analytics research is often institutionally specific examining single-use initiatives for prediction of students at-risk; such research can be difficult to scale and transport beyond the home institution. As a result, universities that incorporate these "big data" initiatives into their plans often rely on outside platforms such as those available from the Education Advisory Board (EAB) to provide the predictive results in easy-to-use dashboard form Georgia State

University is one such school where the Graduation and Progression Success (GPS) initiative provided an early warning system that updated students' grades and records nightly, pushing notifications to advisors in cases in which a student was flagged as being at risk. The initiative increased graduation rates by 10%, decreasing the time to degree, closing the graduation gap for low-income, first generation, and minority students; the initiative also increased STEM major success (Kamenetz, 2016; Bailey, Vaduganathan, Henry, Laverdiere, & Jacobson, 2019). The University of South Florida increased its 6-year graduation rate from 48% to 73% from 2008-2018 by integrating learning analytics into a cross-functional plan to address persistence and graduation rates (Dosal, 2019). However, because these initiatives have incorporated learning analytics along with a suite of other university-wide tools and initiatives to address student success, it can be difficult to determine the direct gains due specifically to the learning analytics tools.

Politico referred to this use of big data as the "Moneyball" solution for higher education (Hefling, 2019). Eduventures reported that these efforts have developed into a \$500 million market for the learning analytics industry, with colleges typically paying hundreds of thousands of dollars to the more than 30 for-profit companies that sell learning analytics tools (Barshay & Aslanian, 2019).

We have found an alternative approach through our research using Realizeit, an approach that bridges the worlds of adaptive learning, learning analytics, and institutional context. Because adaptive learning platforms can generate detailed and real-time data regarding student behaviors, engagement, and performance in a course, these platforms can provide a rich source of information that can help "predict" students' levels of success. The challenge is predicting students' performance early enough to intervene prior to students having too little opportunity to correct their behaviors.

THE PARTNERSHIP

The University of Central Florida (UCF) is one of 12 universities in Florida's State University System. Over 69,000 students attended during the Fall 2019 semester. UCF is a diverse, Hispanic serving institution with 50% first time in college students, 48% minority enrollment and an average age of 23.7 (UCF Facts, 2019).

Colorado Technical University (CTU) is a for-profit university providing industry-relevant programs to approximately 25,000 students. Students within CTU's diverse student body are mostly online learners with an average age of 36.

Both UCF and CTU have extensive support for faculty members who are utilizing adaptive learning, including instructional designers who help faculty focus on the pedagogy for utilizing various technologies. Both universities use Realizeit, with CTU beginning in Fall 2012 and UCF beginning in Fall 2014.

Realizeit is an adaptive platform that allows existing content to be integrated within, or new content to be created within the framework of the platform. The platform can adapt to incorporate distinct characteristics of each instructor, course, or institution's instructional design schema, an outcome the platform achieves by separating content from curriculum (Howlin & Lynch, 2014). Realizeit creates a map (the Curriculum Prerequisite Network) that provides students many alternative pathways to move through the course concepts based on students' real-time knowledge.

HOW COLLEGE ALGEBRA BECAME ADAPTIVE AT UCF

College Algebra at the University of Central Florida (UCF) requires students to sit for a mathematics placement examination. Should they not meet the department requirement, a noncredit intermediate Algebra (IA) course becomes prerequisite. Despite that precondition, at the time of this data analysis, nonsuccess in Algebra (a grade of less than C or better) for students enrolling directly or through IA was approximately 41%. Students' odds of success are favorable but only marginally (about 1.4:1). Therefore, improving the potential for success motivated UCF to adopt the Realizeit adaptive learning platform as the structural foundation for the course.

Realizeit is content agnostic; therefore design within Realizeit requires that course learning materials be created or imported from previously published works. UCF's decision to create the adaptive college Algebra course content provided the institution with an opportunity to personalize the learning materials in a manner that addressed the common student complaints regarding textbook readability, course relevance, and rising textbook costs. The course was designed to incorporate objectives-based learning, alternate content for each of the lessons, and procedurally generated (algorithmic) questions. These course characteristics, along with the adaptive features of the Realizeit platform, collectively fulfil the UCF Adaptive Learning Design Framework (Figure 1).

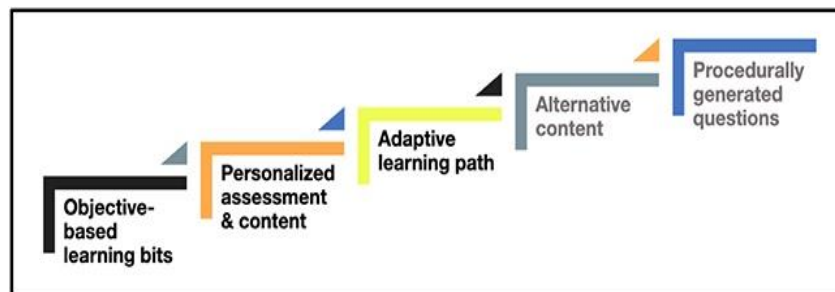


Figure 1. The UCF Adaptive Learning Design Framework

When creating the materials for college Algebra, UCF faculty, instructional designers and support staff broke down each course objective to a consistent granular level to form the associated learning bits (lessons). For example, *operations on functions*, one of the course topics required as a mandate imposed by the Florida State University System, was organized into lessons on finding the sum of functions, difference of functions, product of functions, quotient of functions, and composition of functions. Each lesson was designed to take between 20 and 30 minutes; each lesson was followed by a short formative assessment (check of understanding). In an effort to make the content understandable, course designers insured that the lesson vernacular was stated simply, and that pop-ups were embedded within each lesson to provide vocabulary definitions, mathematical properties, and formulas, when appropriate.

At the start of each assignment, students were called upon to complete a set of targeted questions (determine knowledge) that represented the objective-based lessons contained in the assignment. Based on the results of the answered questions, the student settings, and their previous work, the adaptive platform delivered personalized content and assessments to the individual student. While personalized assessment and content is often based on the results of pretest(s) and/or graded assessment(s) (Essa, 2016), the level of personalization in the UCF college Algebra course is unique because the content is personalized to UCF as well as to the student. Examples unique to UCF were mentions of notable locations, events, and programs specific to the University in the lesson examples and exercises. Because UCF has a diverse student population, name banks were used in examples and exercises that proportionally were representative of student demographics and gender were used. To address student concerns regarding course relevance, the application problems (word problems) included in practice exercises and assessments were personalized to the individual student's program of study. This was accomplished by a two part process. During the question build, nine versions of each application problem were created. The mathematics were consistent across the nine versions, but each of the versions were tailored to have a scenario representative of each of the nine identified programs of study (Arts & Humanities, Business Administration, Education & Human Performance, Engineering & Computer Science, Natural Sciences, Nursing & Healthcare, Hospitality Management, Social Sciences, and Public Affairs). The second part of the process required each student to identify with one of the nine programs of study in their personalized settings. When the student was delivered an application problem, the scenario of the problem was related to that student's identified program of study. In a sense, the result was a sense of increased value-add, since the context presented to each student related the content of the mathematical problem to the student's planned future career.

Students enrolling in college Algebra at UCF have varying levels of understanding and different knowledge sets. In any given class, some students need only a quick review of the learning objective content while others benefit from a full review of prerequisite material prior to attempting the associated content. The adaptive learning pathway includes prerequisite learning materials and an acceleration or remediation capability that adapts to students' knowledge level. Utilizing an accelerated timeline, students were able to complete multiple courses within one semester thereby reducing time to graduation. The platform also provided learning analytics while recommending personalized interventions that the instructor could review at the course, lesson, and student level.

When creating the lessons, designers included alternative adaptive content presentation types (text, pencast, and video). Students were delivered the initial presentation type based on learning performance and learning characteristics but also were provided the option to request an additional presentation, if desired. Given that some students repeated a lesson multiple times, the learning content was designed to be algorithmic.

The last of the five features included in the course were procedurally generated questions. Algorithmic, worked-out examples were built to include every step of a problem solution, with associated explanations. Similar algorithmic examples were created by removing the trivial steps and then providing associated explanations. The adaptive platform used preset conditions to deliver very detailed, step-by-step, worked-out examples to the struggling student, in hopes of preventing at-risk students from becoming lost, whereas the platform delivers to the stronger, higher performing students a similar example with the trivial steps and explanations removed.

THE SEARCH AT UCF: ACTIONABLE VARIABLES

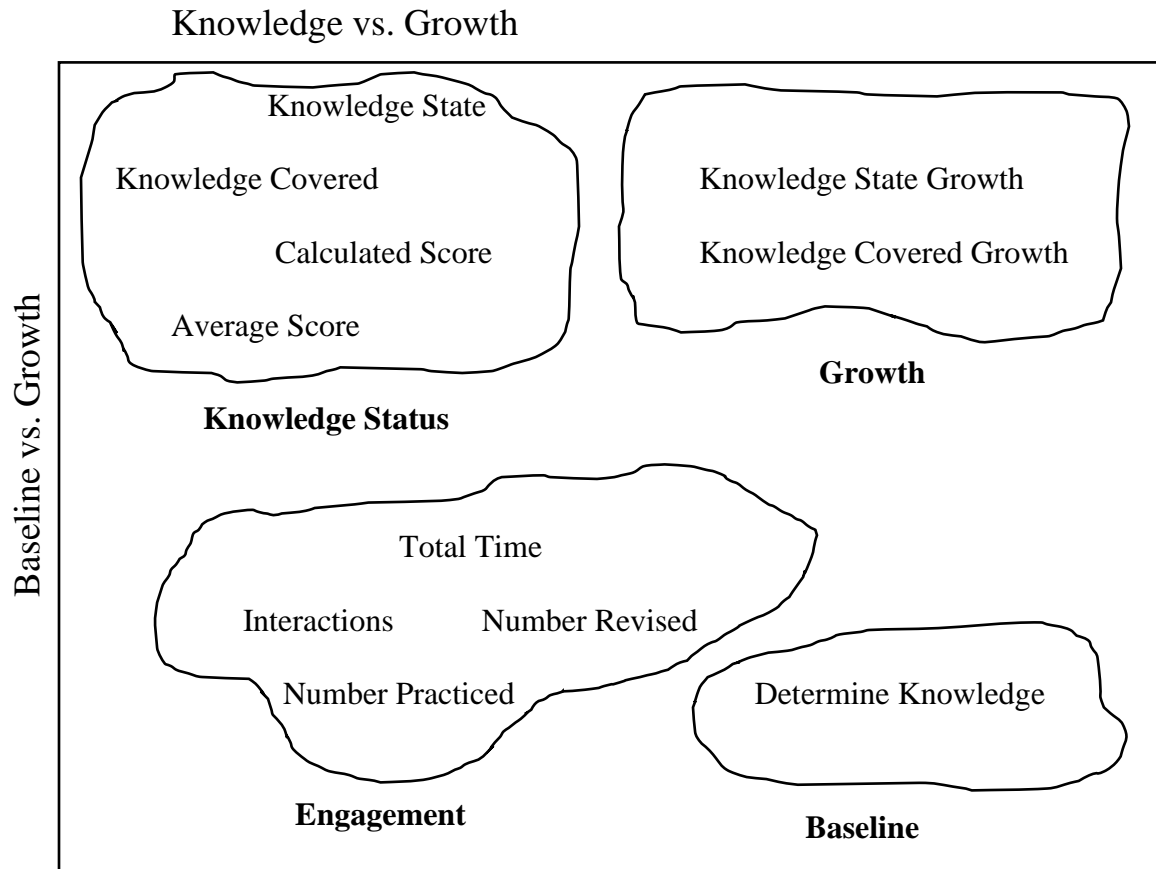
Realizeit assembles many student performance and engagement indicators 'under the hood' and makes them freely available to clients. Because the data are uniformly collected, verified, and scaled in a readily usable manner, organizations such as the Research Initiative for Teaching Effectiveness (RITE) at UCF have experienced a cooperative advantage when in engaging in developing effective learning analytics models. The objective of this study was to find through use of the Realizeit suite the most effective and actionable variables for predicting and facilitating student success in college Algebra. The indices used for modeling development are defined in Table 1.

Table 1. Realizeit Metrics - Explanation of Variables

Variable	Explanation
Knowledge State (KS)	A measure of student ability. The mean level of mastery that the students have shown on topics they have studied.
Knowledge Covered (KC)	A measure of student progress. The mean completion state of each of the course objectives.
Calculated (CA)	An institution-defined combination of several metrics, mainly KS and KC, used to assign a grade to students.
Average Score (AS)	The mean result across all learning, revision, practice, and assessment activities.
Determine Knowledge (DK)	The percentage objectives on which the student completed a Determine Knowledge operation.
Knowledge State Growth (KSG)	The extent by which a student's KS has changed from the start of the course. Can be positive, negative, or zero.
Knowledge Covered Growth (KCG)	The extent by which a student's KC has changed from the start of the course. Can be positive or zero.
Interactions (IN)	The engagement level of the instructor(s) with the student. The total number of interactions.
Total Time (TT)	The total time spent on non-assessment activities started by the student.
Number Revise (NR)	The total number of node-level activities that are classified as revision.
Number Practice (NP)	The total number of objective-level practice activities.

The first step in the modeling development process was to configure the relationship among the eleven Realizeit indices in a scaled visual space using the multidimensional scaling process (Borg, Groenen, & Mair, 2018). This approach facilitates interpretation of viable latent clusters, their relationships, and how this configuration ___ might inform further procedures.

The results of that analysis are presented in Figure 2.



$R^2 = .98$

Stress = .003

Figure 2. Smallest Space Configuration of Realizeit Indices

For the two-dimensional solution, one cluster (upper left) of variables reflected knowledge acquired while another configuration (upper right) depicted student growth. A third group of indices (center position) assessed student engagement with the learning platform. The single variable “determine knowledge” (lower right) measured students’ baseline standing. The configuration produced low stress (.003) on the system and a high squared multiple correlation (.98), meaning that the two-dimensional portrayal produced a close approximation to the ordered pairwise Euclidian distances in the entire variable set. The horizontal dimension illustrated the counterpoised relationship between acquired knowledge and growth. The vertical dimension demonstrated a similar oppositional relationship between prior status (determine knowledge) and growth as well. The engagement variables were located equidistant from the achievement and growth clusters as well, being equidistant from the baseline status of the students, impacting each to a

similar degree. This scaling validated the measurement proposition that pretests are negatively related to gain scores and that students entering the course at the highest levels gain the least (Harris, 1962). This solution was initially encouraging because it suggested that students requiring the most predictive analytic assistance (low pretest and least knowledge acquired) might have the most to gain. Furthermore, this procedure identified the possible influencing variables independently from other considerations such as academic history. However, because research suggests that grade point average exerts a strong mediating influence on these procedures (Moskal, Cavanagh, Wang, & Zhu, 2020). Therefore, UCF grade point average was included within subsequent analysis procedures.

THE NEXT STEP: A SUGGESTED MODEL

The study continued with a two-level procedure designed to identify which of the Realizeit indices mediated by GPA best predicted student success and to obtain some indication of the predictive accuracy of the Realizeit indices. The first step incorporated classification and regression trees (CRT), (Breiman, Friedman, Olshen, & Stone, 1984), a data-mining technique that pinpoints classification rules for identifying which variables best predict success. To deal with missing values, the user does not have to impute values because decision trees have built-in mechanisms, such as floating category approaches. Decision trees are excellent methods for studying problems such as the problem under considering because decision trees determine which variables do the “prediction heavy lifting” for success.

The follow-up analysis used the variables identified in the decision tree process in a logistic regression for dichotomous (binary) success in which one or more of the predictors are nominal, ordinal, interval or ratio-level independent variables. This was a screening process intended to give some direction for further development of the predictive models. The CRT procedure identified three variables that were most effective at predicting success in college Algebra at UCF:

- Grade Point Average (GPA)
- Total Number of Items Revised (Number Revised)
- Total Time Spent in the Course (Total Time)

Those three variables had an overall prediction accuracy rate of 77%. Using those three indices in the logistic regression model yielded a 77% prediction accuracy as well (Osborne, 2014). Therefore, GPA, revision, and total time form the foundation for this study. However, in order to build more effective classification models, the three identified variables were converted to quartiles so that the gain for analytic cohorts might be more accurately identified. In addition, this process permitted a test of greatest predicted gain for the lowest performing students versus those that demonstrated an initially high achievement level. We sought to determine if what we developed would help those in most need by improving their odds of success.

Table 2. Algebra Success by GPA, Total Time and Number Revised Quartiles

	Q1	Q2*	Q3*	Q4
GPA	26%	59%	63%	88%
Total Time	29%	61%	64%	78%
Number Revised	17%	64%	71%	78%

*Q2-Q3 N.S. for all three variables.

Table 2 presents the success rates in college Algebra (independently) for the GPA, Total Time and Revision quartiles. The patterns appear similar for all three indices. Quartile one achieves significantly lower ($p=.001$) success rates. Bonferroni pairwise post hoc comparisons identified non-significant contrasts. Cast in odds ratio context, the odds of a student in GPA Q1 not succeeding is almost 3:1 where conversely, a student in the top quartile has a 7:1 chance of succeeding. Total time conveys the same story: students in Q1 had 2.4:1 odds of nonsuccess but students in Q4 had a 3.5:1 chance of success. Number Revised follows similarly. In Q1, students had 5:1 odds of nonsuccess, while those in Q4 enjoyed a 5:1 chance of succeeding. The reader should remember that the impact of these indices was assessed in isolation. Their interaction was not considered; rather, analyzing them independently showed the dominant impact of the external variable GPA on student success.

Using the variables identified in the screening process, the authors used CRT to develop a set of predictive rules for determining the likelihood of nonsuccess in the college Algebra course. Noting the strong influence of GPA, GPA was used a mediator throughout the process. The results of those analyses are presented in Tables 3 through 6. Table 3 depicts the decision rule that emerged with all three variables as predictors, confirming the strong influence of GPA, with the percent of non-success independent of each rule included in the table heading.

Table 3. Nonsuccess in UCF College Algebra (41%)

	Q1	Q2	Q3	Q4
If				
Number Revised		•	•	•
GPA				•
Then				
Nonsuccess= 7%	n=495			

Given that the general non-success rate was 41%, the rule indicates that if students are in Q2 through Q4 for revision and Q4 for GPA, their chance of nonsuccess decreases to 7%. Their odds of succeeding rise to 13:1 (Table 3). Responding to the mediating impact of GPA, the decision rule using revision and total time for those students in GPA Q1 is presented in Table 4.

Table 4. Nonsuccess for Q1 GPA in Algebra 1 (74%)

	Q1	Q2	Q3	Q4
If				
Number Revised		•	•	•
Total Time				•
Then				
Nonsuccess= 39%	n=124			

If students in GPA Q1 can obtain a revision placement Q2 through Q4 and a total time of Q4 then their chance of nonsuccess drops from 74% to 39%, changing their odds of non-success from about 3:1 to a change of success of 1.5:1, better than even and comparable to the class as a whole. This is a dramatic improvement from almost certain failure. What this means is that even students with low GPAs can improve their chances of success if they revise a greater number of answers and spend a lot more time in the adaptive courseware.

Table 5 presents similar results for students in GPA Q2-Q3.

Table 5. Nonsuccess for Q2, Q3 GPA in College Algebra (39%)

	Q1	Q2	Q3	Q4
If				
Number Revised		•	•	•
Total Time				•
Then				
Nonsuccess= 24%	n=248			

Remembering that the Bonferroni procedure showed these two quartile GPA success rates to be non-significantly different from one other, they were treated as a combined group. Their non-success rate was 39%, roughly equivalent to the overall value for the class (41%). However, the rule indicated that if students in this group achieved Q2 through Q4 for revision and Q4 for total time, that their non-success rate decreased from 39% to 24%. Originally, their chance of success was 1.5:1. However, under the rule those odds rise to 4:1.

The final rule is presented in Table 6 and shows the change in odds for students in GPA Q4.

Table 6. Nonsuccess for Q4 GPA in Algebra (12%)

	Q1	Q2	Q3	Q4
If				
Number Revised		•	•	•
Total Time				•
Then				
Nonsuccess= 4%	n=123			

From the screening we learned that there was an independent 12% chance of non-success for these students. However, this rule states that if they obtain Q2 through Q4 for revision and Q4 for total time, then the non-success percentage drops to 4%. The odds of success go from 7:1 to 24:1, virtual certainty.

Table 7 presents the rule-based percentage lift in success chances for each of the GPA quartile groups.

Table 7. Rule-Based Success Gains by GPA Quartiles Based on Number Revised and Total Time Quartiles

GPA Quartile	Q1	Q2-Q3	Q4
Gains	35%	15%	8%

There is a 35% lift for students in GPA Q1, substantially increasing their chance of success. There is a moderate but helpful lift (15%) for students in Q2-Q3 and very little lift for those individuals in Q4 (8%). The rules were most effective for those who needed assistance the most, but, relatively ineffective for those who needed it least.

HOW COLLEGE ALGEBRA BECAME ADAPTIVE AT CTU

In 2012, Colorado Technical University (CTU) began researching adaptive learning as a tool to improve the academic experience for students and faculty in an open enrollment institution. CTU students are predominantly adults with an average age in their mid-thirties. As a result, they have varying degrees of work experience and training knowledge in subject areas. These varying levels of prior knowledge provide a unique challenge for instructors because these instructors teach students with diverse skill sets who may not have been in college for long periods of time. Adaptive learning provided a method to determine the knowledge level of students in a course so that content could be personalized. Dashboards included in adaptive learning tools also provided instructors visual insight into progress of students taking a particular course.

CTU programs are taught in an accelerated model; courses are 5.5 weeks in length and a full-time course load is considered 2 courses every 5.5 weeks or 4 courses in an 11-week quarter. Students are able to study part-time as an option to accommodate other obligations including employment, family obligations, and military commitment. When reviewing adaptive learning vendors, CTU set as priority the ability to implement adaptive learning in a number of courses. Realizeit provided faculty members the ability to create learning maps specific to course objectives as opposed to being provided maps for a particular subject, featured in several adaptive courseware platforms. Faculty at CTU created course content with the assistance of a curriculum design team led by a Vice President of Technology, who was actively engaged in the initial search for a vendor and engaged in the development of courses in collaboration with the Provost and Dean of General Education. Math and English faculty indicated a desire to participate in a pilot with Realizeit and MAT 102 (College Math) and ENG 104 (English Composition) were chosen as test bed courses for an initial implementation that included two course sections.

As noted previously, CTU is an open enrollment institution and students are required to take up to three math courses depending upon their program of study. MAT 102 is a basic math course with wide participation, often taken as a precursor to college Algebra. In 2012, college math faculty opted to pilot a fully online, fully adaptive college math course. The Realizeit adaptive platform provided CTU math faculty with the opportunity to develop content in the course based upon predetermined objectives. Faculty worked with curriculum designers to create adaptive learning maps including hundreds of questions and problems for students to review and complete during the course.

The processes of developing the learning maps was similar to those described by UCF; specifically, course objectives were broken down into granular concepts. A difference in the course development protocols at CTU was the inclusion of five top math faculty in the process to ensure that the perspectives of multiple faculty members were included in the course development. What made course development at CTU substantially different was the fact that courses were to be conducted totally online and at an accelerated pace when contrasted with the blended format and semester timeframe at UCF. CTU students addressed their knowledge of concepts and content determined appropriate to their level of achievement in the assessment index (determine knowledge) components of the course. Initially, remedial content was not included in the learning maps; however, tutoring was available to students through an online math tutoring provider.

Results from the pilot studies provided improvements in DFW rates in both the MAT 102 and ENG 104 courses over several course sessions and the Provost worked with colleges and programs to expand the use of adaptive learning into the general education program. CTU made a commitment provide faculty with the ability to work with CTU's curriculum design team to create content that was specific to course outcomes. At CTU, faculty created a master class that has been provided to all students, resulting in hundreds of participants taking the same course in a 5.5-week time period. The engagement of the Provost and Vice President of Technology in adaptive learning strategies was largely attributable to the perception that, overall, adaptive technology could have a substantial positive impact on students and faculty once the technology was implemented at scale.

CTU – A TIME-CRITICAL SETTING

The UCF data suggested an approach to predictive modeling that provides learners with concrete and learnable actions that impact their odds of success positively. While a UCF course typically lasts 16 weeks, a CTU course lasts just 5.5 weeks. The short length of the terms at CTU produces a much more challenging environment for any predictive model. In this section of the study, we explore the impact of this time constraint on the effectiveness of predictive models.

MODELING

With the CTU data, we built a sequence of models that provided close to a real-time prediction of a student's changing chances of success in a course. This was enabled by building a framework that utilizes accumulated learning data at regular time slices throughout the course. Traditional approaches that build models based on the data at the end of the course are effective for setting expectations of the effort levels needed to give students the best chance of success, but are not particularly useful for setting incremental metrics or providing guidance based on a student's

current progress. A sequence of models can overcome this shortcoming by providing a regular update on the student's real-time chances of success.

For this analysis, data were gathered from over 5,000 students across seven terms in a math course at CTU. The C5.0 algorithm, an improved version of C4.5 (Quinlan, 1993), was used to build models using some of the same Realizeit variables as those used the UCF study, augmented by additional indicators. The models attempted to predict the binary outcome of course success, defined as reaching the required grade set by the institution. CTU bases the final math course grade predominately on the final Calculated Score metric provided by Realizeit at the end of the term.

Table 8 explains the variables used in this analysis. Note that the models use only behavioral and attainment-based metrics that can be gathered by the platform because demographic-based data are generally not available.

Table 8. Variables Used in the CTU Models

Variable	Explanation
Total Time (totalTime)	The total time spent on learning
Number of activities (numActivities)	The total number of activities started
Nodes Attempted (numNodes)	The number of nodes attempted
Node Completed (numComp)	The number of nodes completed
Mean Knowledge Covered (meanKC)	The average KC across all objectives started
Start Day (startDay)	The number of days into the term on which the student started learning
Objectives Attempted (numObjectives)	The number of objectives attempted
Objectives Completed (numObjComp)	The number of objectives completed

The analysis addressed two specific questions:

1. At what point in the course is enough data available to make informed and accurate predictions?
2. How do the models change from one time slice to the next?

ENOUGH DATA

Adaptive platforms gather data on users as they interact with platform services. Realizeit collects highly granular logs of all student interactions with the platform and content. As the data grow, the platform builds a picture of how the student learns and uses that information to personalize and customize the learning experience.

Some interactions and usage types will be more informative than others, and some students will generate more data than others. For example, one student may answer practice questions, while another may engage in passive reading. The platform will gather information on each at differing rates and will, therefore, learn to make more effective recommendations and predictions for one student much sooner than another. This also will be true for the time slice-based predictive models, leading to the question of how much data is needed when building an accurate model that can surpass baseline models.

This analysis used the C5.0 algorithm to build a predictive model for each week of the CTU math course. Data generated by the students from the beginning of the course up to and including the split point such as mid-course were available for each model. The accuracy of all models, including both the C5.0 and simple majority class model, was measured using data from the following term.

The majority class model takes the most common outcome from the previous terms and uses it as the predicted outcome for all students in the subsequent term. If a course has very high or very low success rates, then this baseline model can be accurate. However, it may not be a particularly informative model because it does not provide insights into why students are successful or not.

Figure 3 demonstrates the predictive improvement of the decision tree over the baseline.

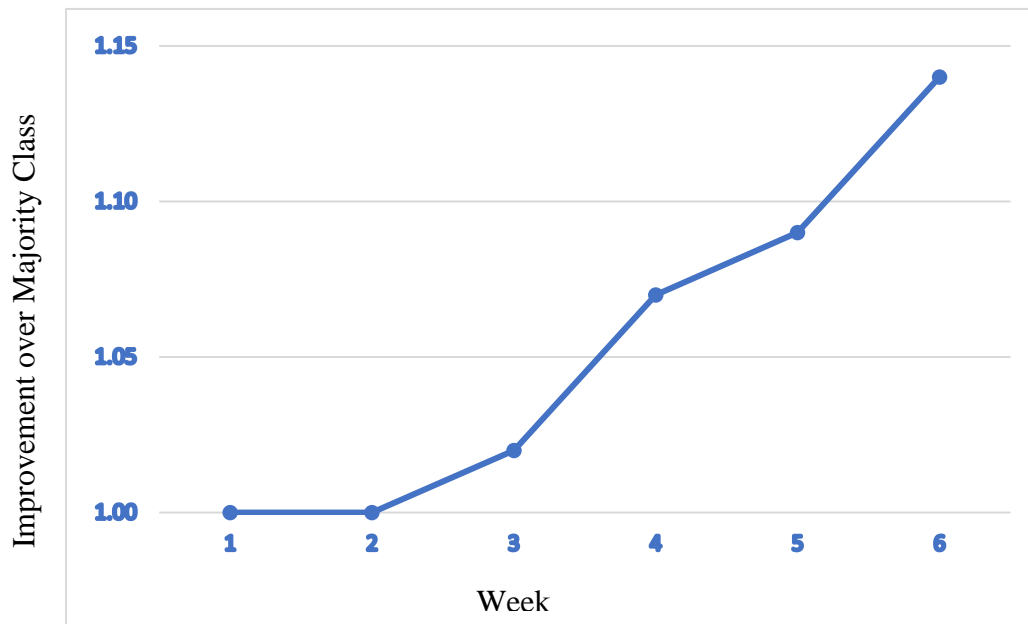


Figure 3. The Improvement Made by the Decision Tree Model over the Baseline Majority Class Model

The ratio of the accuracy of the two models provides a single measure of the improvement of the decision tree model over the simple majority class model. Another way of viewing this is as the payoff for the increased effort of building a decision tree.

For the first two weeks, there was virtually no improvement or payoff. The decision tree model gains no advantage over the majority class approach. Not until week three are there enough data available to beat the baseline. This is the point at which the data have sufficient signal in order to distinguish features that separate those students who will go on to be successful from those who will not. At this point, the model becomes not just accurate but also increasingly informative.

Requiring three weeks of data poses a considerable challenge in the CTU context because it leaves just two and a half weeks before course completion to intervene with students predicted to be unsuccessful. This three-week requirement of data is also present in the UCF context, however, with 16-week courses there is usually sufficient time to intervene.

VARIABLE IMPORTANCE

As seen above, there is a critical threshold at Week 3, after which, on average, there is enough signal compared to noise to make possible a determination with a high level of accuracy the prediction of which students will go on to be successful in the course. Therefore, we can expect the models and variables on which these models rely to vary considerably with an increasingly stronger signal, as the course progresses.

Predictor Importance (Kuhn & Johnson, 2013) allows us to measure how important each variable is to each model. This metric provides a measure of how much signal is present in each of the variables in the model when predicting an outcome. This information is useful for identifying which variables should be monitored most closely by educators to ensure a student is on track for success.

Comparing the time slice-based models enabled the measurement of the change in the predictor importance over time. To simplify the analysis, importance ranking was used rather than raw importance scores. The variables were ranked from most to least important or by strongest to weakest signal, using the raw scores.

Examining the results, there are several noteworthy outcomes. First, several variables, such as the number of objectives completed (numObjComp), start day (startDay), and the number of active days (numActiveDays) remain unimportant across all models/time slices. Those last two are interesting as they could be viewed as seat-time measures but contain little or no signal for course success. Figure 4 summarizes the change in variable ranks.

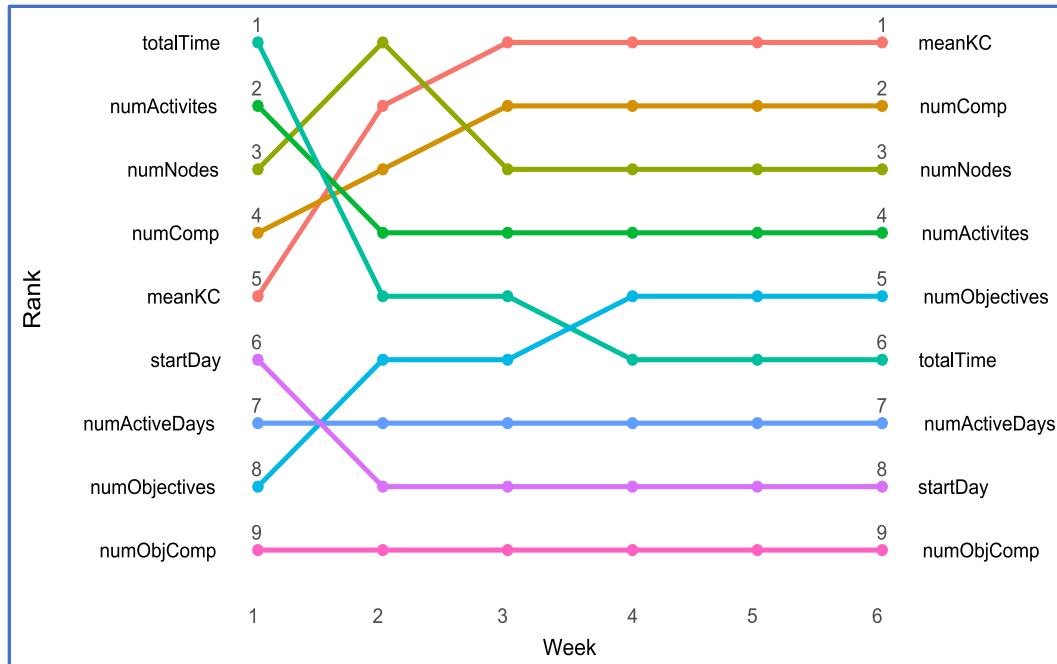


Figure 4. The Ranking of Variables for Importance over Time

Second, measures that capture the quantity of engagement, total time (totalTime), and the number of activities (numActivities) start as important but then decrease in rank over time, being replaced by the metrics that capture the quality of engagement. The number of nodes attempted (numNodes) captures the breadth of the engagement, the number of nodes complete (numComp), and the mean knowledge covered (meanKC) capture how much has been learned.

For educators, the variables that need to be monitored change as the course progresses. Metrics related to the traditional seat-time view were not predictive of student success. While at the beginning of the course, it is important to monitor effort levels, as the course progresses, it becomes more important to monitor the quality of the engagement and the level of progress of students.

CONCLUSION

The results of this study in two universities with considerably different infrastructures and student populations, conducted with their common platform provider, indicated that combining adaptive learning and learning analytics offers promise for helping students achieve successful outcomes in college Algebra. The adaptive framework advantage lies in its ability to personalize the educational experience, customize the content, and provide continuous assessment. Learning analytics in its most effective configuration finds outcome variables that identify

the likelihood of student success early in a course. Ideally, those variables will lend themselves to training, instruction, or orientation. When combined, both approaches to education create a value-added model that benefits students; especially those who, without assistance, are likely to struggle and eventually fail.

Early work by Carroll (1963) paved the way for adaptive analytics, although at the time he proposed his model, learning analytics was yet to be developed or implemented. Consider the fundamental equation in which Carroll (1963) defined learning as the ratio of time spent and time needed.

$$\text{Degree of Learning} = f \left(\frac{\text{Time Spent}}{\text{Time Needed}} \right) \text{ (Carroll, 1963, p. 6).}$$

His expanded notion was:

$$f \left(\frac{\text{Opportunity (Time Allowed)} \times \text{Perseverance} \times \text{Aptitude}}{\text{Time Needed}} \right) \text{ (Carroll, 1963, p. 7).}$$

The three terms in the numerator are key issues for predicting success and can be written in their Venn format as seen in Figure 5.

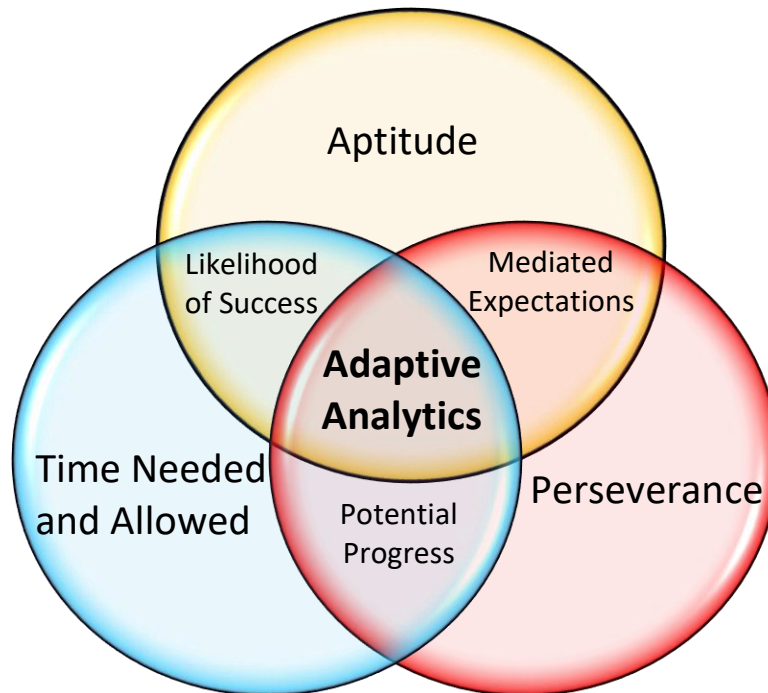


Figure 5. An Intersected Adaptive Analytics Model

The major components of the Carroll model, intersections of aptitude, perseverance, and time (needed and allowed) interact to form the meta-components. Mediated expectations shows that aptitude is not the only determinant because perseverance (engagement) can be an augmenting factor. Aptitude and time interact to provide a better indication of success likelihood. Perseverance and time combine as an indicator of potential progress. In his methods Carroll intimated the construct of learning analytics forming the proposition: If time allowed is constant then knowledge acquired will be the variable. However, if learning is the constant (approximately) then time allowed must be the variable. Put another way, if students spend exactly one 16- or 5.5-week semester in college Algebra then how much they learn, depending on their circumstances, varies. Students have different aptitudes, engage differently, and require different amounts of time to reach mastery.

The question becomes can we develop predictive methods and responsive models that compensate for the many different abilities and engagement idiosyncrasies students bring to their education? If so, what are the mediating student characteristics and behaviors, and is it possible to accommodate them in our instructional approaches? From these two questions, then, a third question emerges: Can an effective system of adaptive analytics be developed with responsive and actionable variables that can function in different contexts such as the University of Central Florida and Colorado Technical University? Further, what role can an adaptive learning platform provide in the support required by universities? Finally, it becomes incumbent on us to identify the level of granularity for which our methods will be most effective. Can we develop learning analytics that are effective for individual students or must we find like-cohorts and make some estimate of the odds of improvement in a general way, attempting to identify the most homogeneous groups possible? This frames the problem of individual versus prototype groups.

The UCF component of this study indicated that the suite of Realizeit indices contain two variables that account for most of the variance in student success: number of question or items revised and time spent engaged in the course. However, in the presence of entering grade point average their effectiveness diminishes. Because of this, UCF chose to use GPA not as a predictor but as a mediator by forming quartile cohorts. In order to be consistent, that declassification scheme was used on revision and time as well. The results from UCF indicate that such a declassification scheme compromises some individual precision but increases effectiveness of finding indicators that can be integrated into instructional protocols, thereby increasing the chances of student success. The best indicator of that outcome is that the UCF model gives students with virtually no chance of succeeding in college Algebra better than even odds. Certainly, there is variability for individuals regarding their chances, but as a whole, to some degree, UCF is able

to ameliorate the academic Mathew effect that comes from being in the top GPA quartile. When GPA is used as a surrogate “treatment effect” it greatly reduces the uncertainty about helping students succeed. Time and revision have fellow travelers that can be effective as well. For instance, revision and practice are highly related and for the most part would accomplish the same outcomes. Revision just happened to emerge as the prime variable in the CRT analysis. There are any number of surrogates for time as well, such as a number of activities, nodes attempted and completed, and objectives attempted and completed, all of which are highly correlated with each other and with time. No variable in this system is unique and one variable effectively can be replaced by another with minimal loss of information. However, the encouraging part is that both revision and time lend themselves to instruction during the course, and can be monitored and incrementally improved. Finally, for the UCF study one should remember that this model was post hoc with index measures harvested at the conclusion of the course. However, the greatest lift for success was achieved for the group that needed it the most. In a more compressed time frame those opportunities diminish considerably.

In fact, the CTU study confronted the problem of time compression full on by, capitalizing on cumulative effect information. As emphasized in this work, end-of-course models (UCF) are excellent for determining prerequisites but are ineffective for continuous student status updates. This corresponds to the fundamental difference between summative and formative evaluation. The CTU work used a different variable configuration from UCF that was amenable to continuous time lag modeling. Given that the CTU course is 5.5 weeks in duration, it might be speculated that some of the indices do little to reduce uncertainty about student success. Secondly, given the compressed nature of the course, it might be further hypothesized that initially informative measures may not sustain their validity as the course progresses. In the CTU study, cross comparing the predictive accuracy of term end outcomes with the dynamic cumulative model indicates a relative informational standoff between the two for the first two weeks of class. In contrasting baseline and cumulative approaches, the information gain doesn’t emerge until about 36% of the course is completed. After that point the information gain is accelerated and steep but there are most certainly exaggerated time pressures for helping students who have encountered difficulties so late in the course.

The second component of the CTU work identified a possibly more challenging aspect of comparing static (UCF) versus dynamic (CTU) predictive analytic models. The information they provide over time changes. So what predicted well at the beginning of the course diminished its importance over time, suggesting that, like the fundamental principles of adaptive learning, an effective adaptive analytics model will require continuous feedback. Although this phenomenon was identified in a 5.5-week course, there is every reason to believe that this will happen in a 16-week semester as well. However, both the UCF and

CTU models point to the fact that some form of time management and engagement through such things as revision activity are fundamental to effective prediction of success in college Algebra, independent of institutional context.

Metaphorically, this study used the “digital learning dust” that the Realizeit platform provides as a matter of course. These data, although assessment based, can be integrated into the instructional paradigm, not only providing predictive power, but also providing opportunities for students to overcome the challenges they encounter. In addition, by choosing the title “Adaptive Analytics: It’s About Time” we make a double entendre that first, emphasizes the importance of proper time use in the learning process. Carroll (1963) and others (Adam 2008; Norberg, Dziuban & Moskal, 2011) have demonstrated how time can be a major contributor to variations in human behavior, including learning. Therefore, the bottom line of this work is that, when mediated by prior achievement, genuine course engagement, combined with time needed, form the fundamental components for learning. The encouraging aspects of these two studies are that those elements identified are treatable student characteristics that can respond to instruction and intervention making a case for giving this approach serious future consideration, now that the concept of adaptive analytics viable, and provides the real possibility of actionable and continuing real-time information. Truly it’s about time.

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Student Perceptions of the Effectiveness of Adaptive Courseware for Learning

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STUDENT PERCEPTIONS OF THE EFFECTIVENESS OF ADAPTIVE COURSEWARE FOR LEARNING

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ABSTRACT:

Despite the increasing research on the effectiveness of adaptive learning courseware by vendors and academic institutions, there are few published, peer-reviewed studies on adaptive courseware that address the student experience and student perception of this teaching and learning tool. Over the course of two academic years, 2017/2018 and 2018/2019, researchers at the University of Mississippi conducted 16 course-based student focus groups and gathered data from 4 end-of-semester surveys to understand how students are experiencing adaptive courseware and whether or not they find it adds value to their education. Our study found that, although students generally find courseware to be helpful in their learning, they do not agree the courseware is adaptive, and they find the benefits of the courseware to be undermined by poor implementation and frequent overpricing.

KEYWORDS:

adaptive courseware, student surveys, learning flexibility, digital learning platforms

DISCIPLINES:

Educational Methods, Educational Technology, Instructional Design

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INTRODUCTION

In May 2016, the University of Mississippi (UM) received a grant from the Association of Public Land Grant Universities (APLU) to implement and scale the use of adaptive courseware in high-enrollment, general education, undergraduate classes. One of the goals of the Accelerating the Adoption of Adaptive Courseware Grant is to increase student learning so students may progress through their degree pathways. Faculty at UM and other grant cohort institutions are conducting research on the effectiveness of adaptive learning courseware through comparison studies with sections that do not use adaptive courseware. Similar studies have been reported by Mihalca et al. (2011), Freeman et al., Eddy (2014), Yarnall et al. (2016), Johanes and Lagerstrom, (2017), Liu, McKelroy et al. (2017), and Suna et al. (2017) among others. Studies reveal benefits of adaptive courseware in particular disciplines and with particular products (Nwaogu, 2012; Hinkle et al., 2018; Griff et al, 2013), but universal research on the benefits of adaptive courseware are less conclusive (Murray et al, 2015; Fontaine et al, 2017).

While these studies have measured student learning and outcomes through summative assessments, the purpose of our research is to explore student perceptions of the effectiveness of adaptive courseware for learning. We chose this topic because there are few published, peer-reviewed studies on adaptive courseware that address the student experience and student perceptions of adaptive courseware, although researchers at the University of Central Florida and Colorado Technical Institute have pioneered efforts in this area (Dziuban et al., 2016; Dziuban et al., 2017). These studies demonstrate student satisfaction with personalized learning in terms of self-pacing, learning guidance, ease of use of the platform, and increased engagement with the content. While these studies include a broad range of disciplines, the courses were online and delivered on a single adaptive platform.

Our study seeks to assess student perception of the effectiveness of adaptive learning platforms in courses delivered face-to-face and on a variety of adaptive platforms. Because the student experience is essential in assessing promising, but untested educational initiatives (Swing & Ross, 2016), we feel it is important to understand how students are experiencing adaptive courseware, and whether or not they find it adds value to their education.

As reported in the *2019 Educause Horizon Report*, “Adaptive learning has been a staple in the *Horizon Report* since 2015” (p.34), and was projected to have wide adoption in higher education by 2018. However, in the *2018 Horizon Report*, the timeline was pushed back 2-3 years. There are several reasons outlined in the *Horizon Report* for this change, including the amount of resources required to implement adaptive courseware, the cost of the adaptive courseware which is passed on to students, and the lack of universal evidence of adaptive courseware’s efficacy following several years of hype by vendors, educators, and higher education support institutions. (Alexander et al., 2019) We find the student experience of adaptive courseware at the University of Mississippi aligns with the findings of the *2019 Educause Horizon Report* regarding cost and resources.

ADAPTIVE COURSEWARE AT THE UNIVERSITY OF MISSISSIPPI

INSTITUTIONAL CONTEXT

The University of Mississippi (UM) is an R1 research institution located in the city of Oxford, Mississippi, and surrounded by rural areas. Four regional campuses and a medical center in the capital city, Jackson, make UM a dominant presence in northern Mississippi. The undergraduate student population of 17,000 consists of mainly traditionally-aged students, 38% of whom are Pell-eligible and 22% who are first generation college students. The racially minoritized undergraduate student population at UM is currently 23% of the undergraduate population. This includes the following racial categories on which the institution collects data: African American, American Indian, Asian, Hispanic or Latino, Native Hawaiian or Pacific Islander, Two or More Races.

COURSES INVOLVED IN THE STUDY

UM began piloting adaptive courseware in Spring 2017, reaching scale in several courses by Fall 2018. The chart below lists the courses that adopted adaptive courseware during the grant period. The end-of-semester survey (provided as Appendix A titled) was sent to all students enrolled in these courses and to students enrolled in courses using adaptive courseware in the subsequent semesters discussed in this study. (See Appendix A for a copy of the end-of-semester survey administered in each case.)

Table 1

Courses involved in Adaptive Courseware Grant

STEM	Humanities	Business	Social Sciences
Anatomy & Physiology	Health Ethics	Accountancy I & II	Microeconomics
Biological Sciences	First Year Writing I	Business Statistics	Intro to Sociology
Gen Biology I	European History	Mgmt Info Systems	College Success
Gen Biology II	Elementary Spanish		
Gen Chemistry	Intermediate Spanish		
Intro to Chemistry			
Organic Chemistry			
College Algebra			
Statistics			
Trigonometry			
Calculus I & II			
Quantitative Reasoning			
Gen Physics I & II			
Engineering Fluid Mechanics			

COURSEWARE

While there is currently no standard definition to assess which products can be categorized accurately as adaptive courseware and which cannot, per the terms of the Adaptive Courseware Grant, the University of Mississippi adheres to an approved vendor list compiled by the Bill & Melinda Gates Foundation under the advisement of the Courseware in Context Framework Primer developed by Tyton Partners, a consulting firm specializing in education, information, and media markets (Tyton Partners, 2016).

Digital courseware is instructional content that is scoped and sequenced to support delivery of an entire course through software built specifically for educational purposes. It includes assessment to inform personalization of instruction and is equipped for adoption across a range of institutional types and learning environments (Tyton Partners, 2016, p.3).

Additionally, the Courseware in Context Framework assesses courseware products according to six distinct levels of functionality highlighting adaptivity as a function of the learning tool rather than as a function of instructor or student behavior:

1. The courseware adapts the goals or standards for learner completion, based on more inputs than a single correct response to the previous item or activity.
2. The courseware adapts the presentation of content, based on learner-declared goals.
3. The courseware adapts the complexity or presentation of content, based on a learner pre-test.
4. The courseware adapts the complexity or presentation of content, based on a learner's affective state.
5. The courseware adapts the scope of instruction (breadth and depth of content), based on more inputs than a single correct response to the previous item or activity.
6. Educators or course designers can override or change the parameters of adaptive protocols.

Courseware assigned in UM courses includes Pearson's Mastering and MyLabs, McGraw Hill's LearnSmart and ALEKS, Cengage's MindTap and Open Now, Realizeit, Smart Sparrow, Wiley Plus with Orion, Lumen Waymaker, Hawkes Learning, and Macmillan's Learning Curves.

METHODOLOGY

FOCUS GROUPS

The methodology for analysis of focus group transcripts was a combination of sign-vehicle analysis and evaluation coding. Sign-vehicle analysis involves three measures: the frequency with which a symbol or idea appears, the relative balance of favorable and unfavorable attributions regarding a symbol or idea, and the kinds of qualifications and associations made with respect to a symbol or idea, (Krippendorff, 2004). In our analysis, we noted the frequency and intensity of student comments, and organized these comments into themes which were applied as codes to develop qualitative data in order to assess the focus groups' judgement of the features of adaptive learning (Rallis & Rossman, 2003).

Program evaluation is "the systematic collection of information about the activities, characteristics, and outcomes of programs to make judgments about the program, improve program effectiveness, and/or inform decisions about future programming. Policies, organizations, and personnel can also be evaluated" (Patton, 2002, p. 10). To Rallis and Rossman, evaluation data describe, compare, and predict. Description focuses on patterned observations or participant responses of attributes and on details that assess quality. Comparison explores how the program measures up to a standard or ideal. Prediction provides recommendations for change, if needed, and suggests how those changes might be implemented.

In our focus group sessions, we asked particular questions for the purpose of evaluation of courseware including how adaptive courseware was integrated in classes, what features of the courseware students found useful, and what user feedback students wanted communicated back to faculty.

Table 2

Academic status of students participating in focus groups

Academic Status	Round 1 Fall 2017	Round 2 Spring 2018	Round 3 Fall 2018	Round 4 Spring 2019	Sum	Percent of total
First Year		3	5	2	10	12%
Sophomore	15	4	7	7	33	39%
Junior	8	6	7	5	26	31%
Senior	7	4	3	1	15	18%

Table 3

Demographics of students participating in focus groups

	Round 1 Fall 2017	Round 2 Spring 2018	Round 3 Fall 2018	Round 4 Spring 2019	Sum	Percent of total
Asian	1	1	1	4	7	8.3%
Black	2	6	5	2	15	18%
Latinx	3				3	3.5%
white	25	10	15	9	59	70.2%
Female	24	13	20	11	68	81%
Male	7	4	1	4	16	19%

STUDENT SURVEY

Our research subjects were undergraduates enrolled in face-to-face courses utilizing adaptive courseware. Students were recruited based on class enrollment and were contacted via email. Participation in the student survey was voluntary.

The purpose of the survey was to scale and quantify feedback from the student focus groups, which averaged 3-5 students from each course. By offering a survey to all students using adaptive courseware at UM, we have been able to obtain feedback from hundreds of students in a short span of time. This immediacy of feedback stands in contrast to focus group feedback, which involved far fewer students, and took much longer to obtain, organize, and analyze.

RESULTS

During the final two weeks of the Fall 2017, Spring 2018, Fall 2018, and Spring 2019 semesters, we deployed a 20-question survey to all students enrolled in sections of courses using adaptive courseware. (See Appendix A.) The response rate for the first three surveys averaged 14%, but in the case of the fourth survey, the response rate dropped significantly to 4.7%.

While the demographic make-up of survey respondents generally reflects that of the university, in the cases of the Fall 2017 and Spring 2018 surveys, the ratio of minoritized student respondents to white student respondents was slightly higher than the overall university population.

Table 4

Ratio of minoritized and white student survey respondents AY 2017/2018

Survey respondents by semester year	Ratio of minoritized to white students
Fall 2017 survey respondents	25:74
Spring 2018 survey respondents	26:74
Academic year 2017/2018 population	23:77

The ratio of minoritized student respondents to white student respondents fell below the ratio of the university population for the Fall 2018 and Spring 2019 surveys.

Table 5

Ratio of minoritized and white student survey respondents AY 2018/2019

Survey respondents by semester year	Ratio of minoritized to white students
Fall 2018 survey respondents	23:77
Spring 2019 respondents	19:81
Academic year 2018/2019 population	24:76

Student respondents also over-represent both the Pell-eligible population at UM and the national average of first-generation students at 4-year institutions.

Table 6

Percent of Pell-eligible survey respondents in the UM population

Pell-eligible respondents	Survey	UM population
Fall 2017	43%	26%
Spring 2018	44%	26%
Fall 2018	39%	24%
Spring 2019	39%	24%

Table 7

Percent of first-generation survey respondents in the UM population

First-generation respondents	Survey	Nat avg. at 4-year inst.
Fall 2017	23%	20%
Spring 2018	26%	20%
Fall 2018	23%	20%
Spring 2019	23%	20%

Across all four surveys, respondents consistently ranked the following as the most highly useful features of courseware: supporting multiple attempts at taking quizzes, homework practice, instant feedback, and viewing solutions to problem sets. Also highly ranked as useful features were lesson progress meters, and ‘chunked’ content, a term describing the strategy of breaking up content into shorter, bite-size pieces that are more manageable and easier to remember (Miller, 1956).

In all four end-of-semester surveys, respondents identified “more flexibility in submitting homework and quizzes” as the number one way in which the courseware changed how they learned, and “more flexibility for learning and practicing course concepts” as the second most effective way the courseware changed how they learned. Flexibility in both cases can be defined as having choices in terms of *when* to learn and take assessments, and more choices in terms of modalities for content delivery and practice, the *how* of learning.

In the first year the survey was administered, just over 43% of responding students reported the courseware contributed to their grade being higher than it would have been without the courseware. In the second year, that percentage increased to 49.7% (Fall 2018) and 48.7% (Spring 2019). The percentage of students who felt their grade was about the same with or without courseware remained steady between 39.74% - 42.66%. Each semester of the survey, the percentage of respondents who felt their grade was worse due to the courseware decreased from 14.27% (Fall 2017), 12.79% (Spring 2018), 10.56% (Fall 2018), to 9.13% (Spring 2019).

Another consistent report concerned how faculty were implementing courseware. In all four surveys, students reported faculty were using courseware as a homework and quizzing platform and as a textbook replacement. Even so, over 50% of students in AY 2017/2018 reported being directed to purchase a physical textbook to supplement the ebook. This percentage dropped to just over 40% in the following academic year, showing that faculty were responding to student concerns about the additional cost of physical textbooks. Unfortunately, the cost of courseware, with or without a physical textbook, remains high. According to a 2016 survey reported by SRI, after the first year of implementation, “adaptive courseware was associated with lower ongoing costs” (Yarnall et al, 2016. pg. iii). However, that study measured several cost factors including faculty training and technological support costs. Our cost measurements single out the actual price students paid for access to adaptive learning products. Across all four surveys, an average of 73% of students reported paying \$75.00 or more for courseware access, and 53% of students reported paying more than \$150.00 for courseware access.

Filtering the surveys for minoritized students did not reveal significant differences in responses. Moreover, the category of minoritized students is not mutually exclusive from the two other filtered categories, first-generation respondents and Pell-eligible respondents.¹ That said, treated as a discrete category, minoritized students were far more likely to report their grade was higher

¹ See Appendix C for percentages of survey respondents who were categorized in overlapping categories involving two or more of the following categories: Minoritized students; First-generation students; Pell-eligible students.

because of the courseware than the unfiltered student population. In addition, while minoritized students similarly rated flexibility in submitting homework and quizzing as a feature that changed the way they learned, minoritized students noted as helpful for their learning the ability to complete coursework on a mobile device and the opportunity to practice concepts the courseware identified to them as areas in which their mastery was weak.

First generation responding students were aligned with the unfiltered survey respondent population in terms of the two of the top three most useful features of courseware first generation survey responders identified: being able to take quizzes more than once and homework practice. However, unlike the unfiltered population, first generation students consistently ranked the progress bar as either the second or third most useful feature of courseware. Among the top three ways the courseware changed the way they learned, first generation respondents listed a. flexibility in submission dates for homework and quizzes, and b. flexibility in learning course concepts and in practicing those course concepts. However, they differed from the minoritized population by listing c. 'revising lessons for a higher grade' as a way the courseware changed the way they learned.

First generation respondents aligned with the unfiltered population in reporting their grades as positively affected *by* courseware each consecutive semester. However, they did not report a steady improvement in their grades *due to* the courseware. Those in spring semesters reported a more positive effect on their grades due to the courseware than those in the fall semesters. As we explain below, students differentiate grade gains made from increased learning from grade gains obtained through increased opportunities to earn additional points on assessed work.

Pell-eligible responding students found homework practice and the ability to take quizzes more than once to have been useful features of courseware. However, they also found the progress bar and solution sets useful features. As with the other groups, Pell-eligible respondents found the flexibility of submission dates and multi-modal ways to learn content changed the way they learned. They also identified revising lessons for a higher grade and accessing alternate learning materials as important to their learning.

Pell-eligible students reported a steady increase in the positive effects of the courseware on their grades. After a spike of 16.67% reporting in spring 2018 that courseware negatively affected their grades, that percentage dropped to 12.29% in fall 2018 and to 10.87% in spring 2019.

STUDENT FOCUS GROUPS

During each of the four semesters of the study, we conducted four student focus groups, with each group focused on a particular course. (See Appendix B). Conducting student focus groups allowed us to drill down into the data provided in the end-of-semester surveys, while also allowing us to identify student concerns specific to particular courses and courseware. Each focus group was audio recorded, and the audio files transcribed. Individually, and then collectively, members of the research team determined major themes in student feedback based on the number of times students spoke about an issue and the intensity with which they made such utterances.

Table 8

Top concerns of the student focus groups by semester

Semester	Courses	Top Concerns Ranked
Fall 2017	Trigonometry General Biology I General Chemistry Anatomy & Physiology	1. Cost and value of the courseware 2. User experience 3. Alignment of courseware with course content 4. Instructor use of courseware
Spring 2018	College Algebra Intermediate Spanish Intro to Chemistry Business Statistics	1. Cost and value of the courseware 2. User experience 3. Alignment of courseware and course content
Fall 2018	Intro to Statistics Microeconomics Organic Chemistry First Year Writing	1. Cost and value of the courseware 2. User experience 3. Alignment of courseware with course content
Spring 2019	Accounting II Biological Sciences II Intro to Sociology Fluid mechanics	1. Alignment of courseware with course content 2. Cost and value of the courseware 3. Instructor use of courseware 4. User experience

Cost and value of the courseware

Because digital learning platforms are classified at UM as course materials, the decision to adopt a particular product is made primarily by course instructors and course directors. As a consequence, negotiations with vendors regarding cost and point-of-sale tend not to be made at the institutional or department level. Courseware costs can vary considerably based on where a student purchases the courseware and how course materials are bundled.

Students who purchase courseware access either directly through the vendor or from a third-party online retailer tend to get the best price and the most flexibility for access codes. In large part, this is due to two factors: courseware being sold separately from a print textbook and the variety of choices students have to purchase variable durations of access to a resource: Durations of access to courseware tend to vary between 6 months and 24 months.

Some departments have instituted a course fee to cover the cost of digital learning platforms, thus allowing students to pay for course fees as a component of tuition rather than as an out-of-pocket expense. The course fee model does not allow students choice in terms of which course materials they prefer (digital or print) or allow students to choose length of access to the courseware, but the course fee model often saves students money since departments negotiate course fees with vendors.

Students who purchase courseware access through the University bookstore often pay the most because course materials packages are often bundled to include a physical textbook with the courseware access code. In addition, the University bookstore markup on course materials tends to result in higher costs than course materials purchased online or at local, competing bookstores.

Every focus group mentioned the high cost of courseware access codes; for members of 14 of the 16 focus groups, cost and value was participants' top concern regarding adaptive courseware. Over the two-year period of our study, access codes sold through the university bookstore averaged \$151.00 for each code. This price average did not account for codes granting access to courseware across semesters. Students informed us that two-semester access did not benefit them when they were unable to register for part II of a year-long course due to scheduling conflicts, or due to not having earned a high enough grade in part I of the course to be allowed to register for part II. For these reasons, multi-semester pricing deals do not necessarily mitigate students' overall cost of courseware access.

Another cost issue is bundled course materials. While some bookstores market first day course materials packages to students as a convenience, students noted how these bundled packages included physical textbooks they did not want but had to purchase because it was the only way to obtain the access code for required courseware.

A related theme of frustration students expressed during the focus groups involved a perceived lack of guidance from advisors, faculty, and bookstore staff regarding which course materials significantly contributed to course success and which did not. Like any savvy consumers, students do not want to purchase items they do not perceive as adding value to their endeavors. First year students, transfer students, and first-generation students are particularly vulnerable to over-purchasing and overpaying for course materials because they do not yet have the university connections to guide them in bypassing bookstore bundles for more economically practical purchasing options.

Across focus groups, students made economic calculations based on the price of courseware and the value of courseware in determining their final grade. In particular, students were frustrated by high-cost access codes for courseware that did not significantly contribute to their final grade in a course. For example, members of one biology focus group expressed their frustration at having paid \$200.00 for courseware that only accounted for 10% of their final grade. However, students in College Algebra characterized the courseware as adding value to their learning. Although they mentioned that the courseware was still expensive at \$92.85, they thought the value the courseware brought to their learning experience was significant. For these algebra students, support tools included in the courseware (diagnostic tests, identifying content with which students struggled, and practice exercises) and the courseware's alignment with high stakes exams in the course increased the courseware's value and justified the high price.

Similar to members of the college algebra focus group, members of both the engineering focus group and the accounting focus group thought the price of their courseware was reasonable. Engineering focus group members did not pay anything for their courseware, whereas members of the accounting focus group had paid over \$100 for 12 months of access to the courseware. Overall, students in professional programs expressed less frustration with the cost of access codes than students taking general education or elective classes. For example, students in Biology I, which is a class for non-STEM majors, felt that paying over \$100.00 for the courseware access code was excessive.

Most focus group participants agreed that \$100.00 is a fair price for access codes for ebooks and courseware in STEM classes, but also stated they wished faculty would try harder to find less expensive course materials. When pressed for a fair price point for non-STEM courseware, students agreed \$50.00 is the high end of what a single text or homework platform should cost.

Some students believed cost of courseware was too high because they believed use of the courseware had not been integrated well into primary course content, and/or felt that faculty members had not utilizing courseware features beyond the rudimentary capability to grade assessments automatically. Students felt

it was wrong to be asked to pay for courseware that was only utilized as a homework platform. For other students, the problem of integration lay with the courseware's misalignment with the content assessed on high-stakes exams. We will expand more on this topic below. A third source of economic frustration identified by focus group participants had to do with faculty members who required the purchase of courseware systems that were not used consistently in a course, or who did not include the evaluation of student work performed within the courseware system in the calculation of the students' final grades. Additionally, students did not find the price of courseware corresponded with its value or effectiveness. Specifically, higher pricing did not mean the courseware was more beneficial in learning or course success. In fact, students in the engineering focus group who paid nothing for the courseware they used seemed to have the most positive experience with the use of courseware.

User Experience

Students in most focus groups found courseware easy to navigate and noted they did not need to view tutorials before using it. The focus of discussion for user experience tended to fall into three categories: grading, personalization, and workload.

In both the student surveys and focus groups, students overwhelmingly expressed not knowing how much their performance in adaptive courseware counted toward their final grade. While this lack of knowledge could be a matter of students not reading what is clearly stated in the course syllabus, we also heard from students in focus groups that instructors sometimes added or eliminated courseware assignments during the semester, making it difficult for them to assess the value that would be assigned to courseware use in the calculation of their final grade.

When we reported this student confusion to faculty members, they lamented how students only seemed to want to perform schoolwork with a grade attached to it. However, when we shared that faculty sentiment back to students, they replied that they have to make careful choices about how to spend their time. In particular, students who work, who have family responsibilities, or who are heavily involved in school organizations must make careful choices regarding the activities they invest time to accomplish. If there is little or no direct value tied to time spent on a learning task, or if the value is unclear, students will choose not to spend their time on that task.

While it was hard for students to assess accurately the impact of the courseware on their final grades, they expressed concerns regarding the impact of performance in the courseware on their overall grade. Some students completed the homework in the courseware to ensure that their work would raise their grade,

but did not view courseware as a study tool or a means to improve learning; they commented that the courseware “functioned more as a grade booster than a learning system.” However, other students commended the courseware’s quick grading turnaround.

Generally speaking, students had a positive reaction to the adaptive features of courseware if those features were present and conspicuous. Participant of the college algebra focus group reported finding the adaptive resources in ALEKS to be mostly helpful. Students liked the way the system focused on the content with which they struggled and they liked being able to prove mastery and skip over content they already knew. Students also liked being able to practice similar examples of difficult content and being able to choose a less difficult level of problem when the current one was too complex. Students using ALEKS liked the agency the system provided. They were able to choose where to go next versus being forced to follow a particular, system-generated pathway. Students liked the step-by-step instructions for solving problems. On the other hand, students reported feeling frustrated if a courseware system did not seem to provide guidance when they were stuck. Students also lamented courseware systems that require very specific answers (for example, to a decimal place) and systems that are not “smart” in terms of misspellings or other minor errors. Some students who did not like the user experience of the courseware reported using outside aids such as Khan Academy to learn confusing concepts.

Other focus groups perceived the personalized aspect of the courseware as limited. For example, the Intro to Chemistry focus group members reported little variety in the questions the courseware posed. Members of other focus groups also reported frustration when the system did not provide useful feedback for understanding how to model a problem or did not demonstrate how to solve a problem with which they were struggling. Students expressed a desire for a step-by-step demonstration of how to solve a problem they repeatedly got wrong. Other focus groups also expressed a desire for additional, non-adaptive features in the courseware such as video tutorials and low-stakes practice for high-stakes exams.

Some students reported feeling overwhelmed by the number of courseware assignments. They noted that even though they tried to maintain focus on the assignments, as one student put it, the number of assignments caused them to “feel burned out.” Some students proposed that having fewer assignments due each night would allow them to work through the assignments more deeply and methodically. It should be noted that some of these comments came from a six credit-hour class in which students may have been struggling with the workload regardless of the courseware.

Conversely, students did not feel burdened by the workload if they perceived the direct benefit of the courseware to their understanding of course concepts and their performance on assessments. For example, the College Algebra focus group did not feel the amount of time spent in their courseware, ALEKS, was excessive and mentioned the usefulness of the courseware in preparing them for high-stakes exams.

Several focus group participants mentioned how they were required to use multiple platforms each semester, and how switching between systems and remembering all of the passwords created an additional intellectual burden. A few students expressed frustration with online course materials, saying they preferred physical textbooks to online systems because there are too many distractions working online. These students also mentioned screen fatigue, unreliable WiFi in their off-campus accommodations, and computers freezing in the campus testing lab, causing them to lose time during a quiz or to forfeit a quiz attempt.

Some students from the Economics focus group said the courseware was too easy, and that they were able to get high scores without experiencing deep learning. One student from that focus group said she learned more effectively when she wrote her responses on paper versus typing them into a computer. Several students reported frustration that instructors assume that their students are far more tech savvy than those students actually are. The fact that students are comfortable with entertainment and social media technology does not necessarily mean those students are comfortable with educational technology. In fact, the high stakes use of educational technology is stressful for students, especially early in a semester when students lack familiarity with a system at time when they are submitting weighty assessments.

However, some students had a more positive view of the courseware, stating that it was good for accountability in that it forced them to space out learning and prevented them from procrastinating. Students in the First Year Writing focus group spoke positively about the usefulness of the courseware, and reported using adaptive modules for homework and for grammar checks for their writing assignments.

Personalization of the courseware and adaptivity were also frequently mentioned by students in the focus groups. In the Statistics focus group, students had the impression that the instructors checked their progress in the courseware only infrequently because grades were infrequently transferred to the LMS, because instructors did not mention how much time students were spending on the platform, and because instructors infrequently mentioned student performance in the courseware. In several of the focus groups, members did not feel their courseware was truly adaptive because they were fed the same practice questions despite mastering them in previous attempts. Students reported that exam questions were

often exactly the same as those on the practice test, that there were no just-in-time resources to help them learn from incorrect responses, and that there was no summary of the learning objectives that they had mastered and that they had not mastered. Additionally, students stated they wished instructors would check the platform in student mode before students used it. Specifically, they wanted faculty members to be alert for system glitches, errors, and limitations.

Interestingly, students did not value adaptivity as much as features that allowed for learner autonomy. Participants in the Biology I focus group and the Accounting focus group both explicitly stated their courseware systems were not adaptive. Biology I students explained that the homework tool randomly assigned each student five questions from each lesson to complete, providing, as one student put it, “a randomized learning experience” instead of a personalized learning experience. On the other hand, some students reported finding adaptive features in their courseware. For the Engineering students, the system provided corrective and helpful feedback when they made an error. The Sociology focus group did not like how the courseware asked before each practice question how sure they were of the answer, relating that they simply clicked through those types of questions without giving them too much thought. In contrast to members of the College Algebra focus group, students in some humanities classes disliked the adaptive feature that let them skip material when they demonstrated mastery on a pre-quiz. These students told us they would prefer not to skip content, and thought that one quiz was not a good measure of what they did and did not know, particularly because often they guessed the correct response.

Overall, students found the learner autonomy features of the courseware more beneficial than the adaptive features. These include the ability to retake quizzes, opportunities to practice and self-remediate, search engines within the textbook, the ability to check why answers are incorrect, and progress measures. For example, one student appreciated a report in the Accounting courseware on how average time spent in the system correlated with students’ grades. This report inspired the student to spend more time in the system to improve his grade. Another student in the Engineering focus group explained that the corrective feedback in the courseware – specifically pop-up messages invoked when a user makes a mistake – was very helpful. The student attributed this helpfulness to the fact that the instructor had written the messages. Since this instructor knew common mistakes students would likely make, these messages were thoughtfully generated, well-integrated, and useful.

Alignment of Courseware with Course Content

Misalignment of courseware content with other course content was a key concern of students in all of the focus groups. Misalignment seems to fall in one of two categories that are not mutually exclusive: generic courseware and instructor-specific lecture notes.

Some misalignment arises from the use of generic courseware. Although many instructors and course directors choose courseware tied to a particular textbook title, oftentimes the courseware content itself is designed to work with a variety of titles in a particular discipline. One student in the General Chemistry focus group noted how she had used the same courseware three years consecutively because it was part of her high school curriculum, and at the university, in a first-year Introduction to Chemistry course and then again in the General Chemistry sequence. According to this student, there had been no significant changes in the courseware system's content, practice examples, or mastery questions from the first time she used it to the third time. This student wondered why a mass-produced product being used so widely was still so expensive. In addition, because the product is used so widely and does not seem to be updated every year, students in focus groups explained how they were able to easily find answers to mastery questions with a simple Internet browser search.

A second category of misalignment concerns instructor-specific lecture notes. Students in our focus groups noted a disconnect between the content delivered through courseware and the content presented in class by their instructors. One student commented that she felt as if she were taking two separate classes on the same topic: one in person and one online. Other students lamented how time spent practicing in the courseware did not prepare them for instructor-written high stakes exams. They gave three reasons for this lack of preparation: the content was not aligned, the problem sets were formatted differently, and the mastery levels assessed in the courseware were much lower than those assessed on in-class exams.

In sum, students expressed frustration that courseware is not customized to a departmental or course curriculum despite the high price tag, and that their work in the courseware is not preparing them for instructor-developed high-stakes exams.

Focus group participants who had recently graduated from high school expressed concern about a shift to learning through the courseware rather than learning in-class. They commented that they perceived a trend toward learning online rather than learning in the classroom and expressed unease over that trend, calling it 'self-teaching.' Students with more years of university, and particularly those in professional and STEM programs, did not share the concern over self-teaching.

In several focus groups, students disliked how the instructor did not review or discuss in class the homework they did in the courseware system, leading them to feel they were completing the courseware quizzes just for the sake of homework points instead of as a tool for understanding. On the other hand, the Engineering focus group members reported the most alignment between the courseware and the class content. Students in that focus group believed this successful alignment was due to the instructor himself having created the content on the courseware platform. Students reported that the instructor could answer adequately all of their questions on material from the courseware and that the courseware quizzes prepared them for the lectures that were given in class. Students in this focus group appreciated the alignment and noted the instructor's investment in the effectiveness of the software.

Instructor use of courseware

A final concern expressed by focus group participants was how instructors were utilizing courseware, namely their underutilization of courseware analytics. When we asked students if they had received individual messages from instructors based on their performance in the courseware, the majority of them said they had not. What we were looking for in this prompt was whether or not faculty are using the learning analytics provided on the instructor dashboard to identify struggling students and to reach out to those students to offer help, suggest tutoring, or simply even to warn students they are in danger of failing the class. Student responses to this question indicated that faculty were not using learning analytics in this manner. However, it is possible that none of the focus group students performed on the courseware in such a way as to prompt a faculty intervention, that faculty interventions were conducted more informally during class time, or that students in need of assistance initiated a help session by attending faculty office hours, thus precluding the need for a faculty-initiated intervention.

In addition to the question about personal messages from instructors, we asked focus group students if faculty members had ever mentioned in class or in a class-wide announcement that they were adjusting a lecture, activity, or assessment based the class's performance reported in courseware learning analytics. None of the students reported having heard faculty say they were adjusting the course based on learning analytics, but again, it could be that these students were taking courses in which adapting a teaching method or assessment was unnecessary, or that the instructor did not explicitly tell students about a change made to course design based on learning analytics.

While it is unclear from the focus group sessions why students were not receiving personalized messages from faculty and why students did not perceive faculty to be tailoring instruction in the class based on learning analytics, we have included this student concern in our report as a means of raising awareness of a

possible issue with faculty underutilization of learning analytics tools. While students understand the difficulties for faculty teaching high-enrollment classes to track individual student progress and conduct personalized interventions, they stated they would welcome personalized messages from faculty. Students in the focus groups expressed a clear desire to form relationships with faculty members, and stated they preferred learning directly from a faculty member to learning from a courseware system.

Students told us they value the effectiveness of an organized, knowledgeable, and available instructor over a good courseware system. Students also appreciated opportunities to talk with instructors about questions they had regarding the course and the courseware. Many students mentioned that a lesson delivered on courseware should not be a replacement for a well-organized lecture or class activity. However, some students mentioned that if they found themselves with an instructor who was ineffective, the courseware became “a back-up teacher”. Students talked about prior experiences with instructors in which they used the courseware as a “lifeline” to supplement their lack of learning in the classroom. However, this seemed to be a last resort, and while some students wavered on the effectiveness of adaptive courseware systems, all the focus group students recognized the importance of effective instructors.

CONCLUSIONS

In both the focus groups and the surveys, more students had positive views than had negative views of digital learning platforms. The courseware features students found helpful were generally those that supported learner autonomy, which they valued more than algorithmic adaptability. Specific examples of these features included ‘due by’ dates rather than one specific due date, multiple attempts for practice and low-stakes assessments, instant feedback on how to solve problem sets, as well as feedback that identified students’ knowledge gaps. The surprising take-away from student responses is that students did not find most courseware systems adaptable. However, while the machines are not adapting to student inputs to provide personalized learning experiences, students are adapting their learning behaviors to both maximize and streamline their learning.

Despite students’ overall positive view of digital learning platforms, they weighed the value of them against two key factors: how well they were integrated into their courses, and how much they cost. When courseware is implemented into a course solely as an add-on for homework practice and quizzing, the content in the system is often misaligned with lecture content, and the systems do not prepare students for high-stakes exams. An equally important consideration for students determining the value of courseware was the cost of access. Students do not wish to purchase products at any price point if those products do not significantly add

value to the learning experience, as for example, when the work students perform in the courseware counts little toward their final grade or does not prepare them for high-stakes exams.

One of the original promises of adaptive courseware is that it will disproportionately benefit underserved students. While our study does not include quantitative data on achievement outcomes, student survey respondents who self-identify as racially minoritized, Pell-eligible, and first-generation reported increasing levels of benefit to their final grade from Fall 2017 to Spring 2019. However, within that time period, there was fluctuation in the percentage of minoritized and first-generation students who believed their final grade was higher due to the courseware. In the Fall 2017 and Spring 2019 surveys, students who were not underserved reported a lower benefit to their final grade than underserved students. In the Spring 2018 survey, it was first-generation students who reported the courseware positively affected their final grade, and in Fall 2018 survey, students who were not underserved reported the greatest benefit to their final grade.

While some of these data are encouraging, they cannot be considered conclusive for three reasons: the data were collected over only four semesters, the numbers fluctuated from semester to semester, and the increasing adoptions of adaptive courseware may have influenced the response rates for any particular survey or focus group question.

Students see value in adaptive learning courseware systems when they are reasonably priced, well-aligned with other course content, and utilized by faculty to respond to student needs. However, students do not view courseware as a substitute for what they value more in their learning: authentic relationships with skilled and caring instructors.

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APPENDIX A: END-OF-SEMESTER SURVEY

Start of Block: Student Demographics

Q1 What is your academic status?

- ☐ First year undergraduate
- ☐ Sophomore
- ☐ Junior
- ☐ Senior
- ☐ Other

Q2 What is your gender?

- ☐ Male
- ☐ Female
- ☐ Non binary
- ☐ Prefer not to respond

Q3 Which ethnic or racial category best describes you?

- ☐ African American or Black
- ☐ African
- ☐ Asian
- ☐ Hispanic or Latino
- ☐ Native American or Alaskan Native
- ☐ Native Hawaiian or other Pacific Islander
- ☐ Two or more ethnic/racial categories
- ☐ White
- ☐ Other

Q4 Are you the first in your immediate family to be on track to complete a 4-year university degree?

- ☐ Yes
- ☐ No
- ☐ Not sure

Q5 Do you qualify for Federal tuition grants or loans such as the Pell Grant? (you don't have to have accepted the grants or loans to answer yes)

- ☐ Yes
- ☐ No
- ☐ Not sure

Q6 Which courseware did you use this semester?

- ☐ Pearson MyStatsLab (Math 115)
- ☐ McGraw Hill ALEKS (Math 121)
- ☐ Pearson MyMathLab (Math 123)
- ☐ McGraw Hill Connect (MIS 309)
- ☐ Pearson Mastering (Chem 101)
- ☐ MyChemLab (Chem 105/106)
- ☐ WileyPlus (Chem 221/222)
- ☐ Lumen Waymaker (Writ 100/101)
- ☐ Lumen Waymaker (EDHE 101)
- ☐ MindTap (Econ 202)
- ☐ MyEconLab (Econ 202)
- ☐ MyStatsLab (Econ 302)
- ☐ McGraw Hill Learn Smart with Connect (Bisc 102/104)
- ☐ Macmillan LaunchPad (Bisc 160/162)
- ☐ Pearson's Mastering A&P (Bisc 206/207)
- ☐ MindTap Physiology (Bisc 330)
- ☐ MySpanishLab (Span 111/211)
- ☐ Cengage Open Now (Soc 101)
- ☐ Realizeit Learning (Phad 395)
- ☐ Pearson Mastering Physics (Phys 213/214)
- ☐ Smart Sparrow (ENGR 323)

Q7 Which functions of the courseware did you find MOST USEFUL in helping you to learn? Check all that apply.

- ☐ The progress tool that told me how much of the lesson I'd completed
- ☐ The learning path or map which showed me what content and activities were in each lesson
- ☐ The multiple ways to learn including video, reading, and interactive tools
- ☐ The way the lessons were broken into small chunks rather than all in one big chapter
- ☐ When the system asked me how well I knew something or how sure I was about an answer
- ☐ Being able to take quizzes more than once
- ☐ Being able to view solutions to problem sets after submitting answers
- ☐ The messages I got from the system telling me "Well done" or "Try again"
- ☐ The ability to choose what I would work on next rather than being forced into a particular learning path
- ☐ The tutorials that broke down concepts step by step
- ☐ The review quizzes
- ☐ The homework practice
- ☐ The instant feedback I got that helped me see what I got right and what I needed to work on
- ☐ The reminders about upcoming homework or quizzes
- ☐ Links to learn more about a topic

Q8 Which functions of the courseware did you find LEAST USEFUL in helping you to learn? Check all that apply.

- ☐ The progress tool that told me how much of the lesson I'd completed
- ☐ The learning path or map which showed me what content and activities were in each lesson
- ☐ The multiple ways to learn including video, reading, and interactive tools
- ☐ The way the lessons were broken into small chunks rather than all in one big chapter
- ☐ When the system asked me how well I knew something or how sure I was about an answer
- ☐ Being able to take quizzes more than once
- ☐ Being able to view solutions to problem sets after submitting answers
- ☐ The messages I got from the system telling me "Well done" or "Try again"

- ☐ The ability to choose what I would work on next rather than being forced into a particular learning path
- ☐ The tutorials that broke down concepts step by step
- ☐ The review quizzes
- ☐ The homework practice
- ☐ The instant feedback I got that helped me see what I got right and what I needed to work on
- ☐ The reminders about upcoming homework or quizzes
- ☐ Links to learn more about a topic

Q9 How would you rate the courseware's effect on your final grade in this class?

- ☐ My grade is lower than it would have been without using adaptive courseware.
- ☐ My grade is about the same as it would have been without using adaptive courseware.
- ☐ My grade is better than it would have been without using adaptive courseware.

Q10 How much does your performance in the courseware count toward your final grade?

- ☐ I am not sure
- ☐ It does not count toward our final grade in the class.
- ☐ It counts less than 10%
- ☐ It counts between 10% and 15%
- ☐ It counts between 15% and 20%
- ☐ It counts between 20% and 25%
- ☐ It counts more than 25%

Q11 Did the courseware change how you learned the material? Check all that apply.

- ☐ I was able to do classwork using a mobile device.
- ☐ I had more flexibility for when I submitted homework and quizzes.
- ☐ I had more flexibility for how I learned and practiced course concepts.
- ☐ I was able to revise lessons for a higher grade.
- ☐ I was able to access alternate materials that helped me understand course concepts.
- ☐ I spent more time practicing course concepts the courseware showed me I was weak in.
- ☐ I was able to skip content I already knew.

Q12 How did your instructor integrate the courseware into your course? Check all that apply.

- ☐ We used the courseware during class time to practice new concepts.
- ☐ We used the courseware during class time to collaborate on projects.
- ☐ We used the courseware during class time to take quizzes.
- ☐ The courseware replaced the textbook.
- ☐ Using the courseware was optional for students who wanted or needed extra help.
- ☐ We used the courseware outside of class to complete assignments.
- ☐ We used the courseware outside of class to collaborate on projects.
- ☐ We used the courseware outside of class to take quizzes.

Q13 Does your instructor discuss your progress or the class's progress in the courseware during class or in an email?

- ☐ Yes
- ☐ No
- ☐ Not sure

Q14 On which device did you most often use the courseware?

- ☐ In a lab, using a university-owned computer
- ☐ On a tablet such as an iPad
- ☐ On my laptop
- ☐ On my desktop
- ☐ On my smartphone such as an iPhone or Android

Q15 How much did your access code cost?

- ☐ More than \$150.00
- ☐ Between \$100.00 - \$150.00
- ☐ Between \$75.00 - \$100.00
- ☐ Between \$50.00 - \$75.00
- ☐ Under \$50.00
- ☐ It was free
- ☐ I do not know

Q16 How do you feel about the cost of the access code?

- ☐ It was overpriced.
- ☐ It was priced about right.
- ☐ It was underpriced.

Q17 Where did you buy your access code?

- ☐ At the official Ole Miss Bookstore (Barnes & Noble)
- ☐ A bookstore other than the official Ole Miss Bookstore such as Rebel Bookstore or Campus Book Mart
- ☐ Online and directly from the publisher
- ☐ Online from a third party such as Amazon, Chegg Books, or another online store.

Q18 Did you purchase a physical book along with the access code?

- ☐ Yes
- ☐ No

Q19 If you bought a physical book, why did you do so?

- ☐ It was a required purchase.
- ☐ It came with the access code.
- ☐ I wanted the physical book.
- ☐ I did not purchase a physical textbook.

Q20 If you purchased a physical textbook, how often have you used it for class?

- ☐ I use it at least once weekly.
- ☐ I use it less than once weekly.
- ☐ I never use the physical textbook.
- ☐ I did not purchase a physical textbook.

APPENDIX B: FOCUS GROUP QUESTIONS

- How has your instructor instructed you to use the courseware? For example, do you only use it to prepare for exams, or use it for homework completion, or is the courseware a replacement for your textbook?
- When you use the courseware, how long does it take you to complete the required lessons?
- Do you feel you spend more time or less on studying/homework/lessons than in classes in which you don't use adaptive courseware?
- Are you more likely to do readings, quizzes, and practice modules when you know a computer system is recording your use?
- Has your instructor ever sent you an email, text, or verbal communication regarding your use of the courseware?
- Do you feel the adaptive features of the courseware are helping you learn the course content? If yes, why do you think that is? If no, how do you prefer to learn course content?
- Have you noticed any difference in your grades in classes in which you use adaptive courseware versus classes in which you don't use adaptive courseware?
- What would you want your instructors to know about the courseware that you feel they don't already know?
- What would you want the university administration to know about adaptive courseware?
- If you had the choice to take a class next semester with or without adaptive courseware, which would you choose? Why would you make that choice?

**APPENDIX C: DATA ON PERCENT OF OVERLAP FOR CATEGORIES OF
MINORITIZED, PELL-ELIGIBLE & FIRST-GENERATION STUDENTS
AMONG SURVEY RESPONDENTS**

Three-way overlap of Minoritized, Pell-eligible, and First-generation college students

Fall 2017 survey:	7%
Spring 2018 survey:	8%
Fall 2018 survey:	8%
Spring 2019 survey:	7%

Two-way overlaps among pairings of Minoritized, Pell-eligible, and First-generation college students

Fall 2017 survey

First gen and minority	9%
First gen and Pell =	15%
Minority and Pell =	17%

Spring 2018 survey

First gen and minority	9%
First gen and Pell	18%
Minority and Pell	17%

Fall 2018 survey

First gen and minority	10%
First gen and Pell	15%
Minority and Pell	16%

Spring 2019 survey

First gen and minority	8%
First gen and Pell	15%
Minority and Pell	13%

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Adaptive Courseware Implementation: Investigating Alignment, Course Redesign, and the Student Experience

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ADAPTIVE COURSEWARE IMPLEMENTATION: INVESTIGATING ALIGNMENT, COURSE REDESIGN, AND THE STUDENT EXPERIENCE

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ABSTRACT:

In this paper, four institutions share student and faculty feedback on the implementation of adaptive courseware through a common case study: biology for undergraduate non-majors. Additionally, each institution has provided a second case study of their choice. Together, researchers at Colorado State University in Fort Collins, CO, Portland State University in Portland, OR, University of Central Florida in Orlando, FL, and the University of Mississippi in Oxford, MS consider student perception of the benefits to the implementation of adaptive courseware, and how the deliberate alignment between adaptive courseware and course organization and structure impacts student experience. This paper highlights the collaboration of four public land grant Universities and includes data from thousands of students across the United States. Our findings indicate that adaptive blended courses with student engagement at the core multiplies opportunities afforded by emerging technologies within blended course design. This paper contributes multi-year data from four institutional approaches to implementing adaptive software to center student engagement.

KEYWORDS:

adaptive courseware, course redesign, blended courses, student engagement

DISCIPLINES:

Educational Methods, Educational Technology, Instructional Design

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INTRODUCTION

In 2012, the Bill and Melinda Gates Foundation (BMGF) made a commitment to helping low-income and first-generation college students achieve postsecondary success. Their aim is to remove barriers that contribute to the education gap including college readiness, affordability, and flexibility. In 2014, BMGF invested \$20 million in a program they called The Next Generation Courseware Challenge (Gates Foundation, 2014). Educational technology companies selected for the challenge designed adaptive courseware that could be scaled for high-enrollment classes. Digital courseware is instructional content that is scoped and sequenced to support delivery of an entire course through software built specifically for educational purposes. It includes assessment to inform personalization of instruction and is equipped for adoption across a range of institutional types and learning environments. Specifically, digital courseware has three core elements:

1. Instructional content that is scoped and sequenced to support delivery of an entire course
2. Purpose-built software
3. Assessment to inform personalization of instruction

These three elements can be delivered in a single product or by the thoughtful integration of different products that collectively deliver a complete course, and that provide faculty with data which allows for further personalization of instructional strategies.

Research in the early stages of adaptive courseware adoption conducted by community colleges, technical colleges, and traditional universities indicated that adaptive courseware used in blended courses (involving some online and some face-to-face time) increased student success (Means, Peters, & Zheng, 2014). More research needs to be done, but the potential of courseware to ensure postsecondary education becomes more accessible to all students convinced the Gates Foundation to move forward with The Next Generation Courseware Challenge.

BMGF provided the Personalized Learning Consortium at the Association of Public Land Grant Universities (APLU) a grant to support large-scale implementation of adaptive courseware at public universities. After an initial RFP conducted in the summer of 2016, eight universities became part of the first grant cohort (APLU, 2017). In an effort to support the efforts of additional institutions to implement and scale adaptive courseware, universities in the original cohort are reporting results of student and faculty feedback on these digital learning tools.

In this paper, four institutions share student and faculty feedback on the implementation of adaptive courseware through a common case study: biology for non-majors. Additionally, each institution has provided a second case study of their choice. Together, researchers at Colorado State University in Fort Collins, CO, Portland State University in Portland, OR, University of Central Florida in Orlando, FL, and the University of Mississippi in Oxford, MS are considering the following questions: What do students perceive are the benefits to the implementation of adaptive courseware? How does the deliberate alignment between adaptive courseware and course organization and structure impact student experience?

UNIVERSITY OF MISSISSIPPI CASE STUDIES

The University of Mississippi (UM) is an R1 research institution located in Oxford, Mississippi, and surrounded by rural areas. Four regional campuses and a medical center in the capital city, Jackson, make UM a dominant presence in the upper half of the state. The undergraduate student population of 17,000 comprises mainly traditionally aged students, 38% of whom are Pell-eligible and 22% of whom who are first generation college students.

Some faculty members at UM have been working with adaptive learning courseware platforms for over a decade, but it has been in the last three years that these digital learning tools have grown in popularity. Although student success is a universal goal, the university is proud to claim a first-year retention rate of 85% and a 6-year graduation rate of 65%. Most faculty adoptions of digital courseware systems result in cases in which a publisher has courseware that accompanies a textbook. In 2016, with the help of a grant from the Personalized Learning Consortium

at the Association of Public Land Grant Universities, UM began supporting faculty members who wished to develop their own content on digital learning platforms, and who wished to better align publisher platforms to their course needs.

At the University of Mississippi, each year, courses that have implemented adaptive courseware account for nearly 18,000 general education enrollments. From the very beginning of the grant and continuing through today, the disciplines with the most enrollments in adaptive courseware have been STEM related, with the majority of these courses taught in the subject area of mathematics.

Figure 1

Enrollments by Field. Enrollments by field in courses using adaptive courseware at the University of Mississippi AY 2018-2019.

Field of study	Percent of UM total enrollments using adaptive courseware AY 2018-2019
Mathematics	25%
Biology	18%
Writing	18%
Chemistry	17%
Accountancy	12%
Economics	6%
Spanish	4%

Figure 2

Enrollments by Discipline. Enrollments by discipline in courses using adaptive courseware at the University of Mississippi AY 2018-2019.

Discipline Area	Percent of UM total enrollments using adaptive courseware AY 2018-2019
STEM	60%
Humanities	22%
Business	18%

Because the administration at UM defines courseware as a course material, faculty have autonomy in choosing courseware and of implementing it within their courses. As such, integration of adaptive courseware does not require oversight by IT, nor is courseware adoption considered a course revision overseen by a curriculum committee. Some departments engaged in a course revision to accompany courseware implementation, notably Writing & Rhetoric, which employs an in-house instructional designer and two college writing specialists. By and large, however, course revision remains faculty prerogative and is faculty driven. This means that in most departments, individual faculty who teach multi-section courses may revise their section without having to coordinate with faculty teaching other sections of the same course. However, course directors of multi-section courses tend to discourage instructors from making significant changes to their section of a course unless those changes can be scaled to all sections of the course. Without the technological and pedagogical support of instructional designers and learning specialists, the coordinated revision of a multi-section course can be burdensome to course directors. While faculty can get technical assistance for certain products such as the LMS through the Faculty Technology Development Center, and although The Center for Excellence in Teaching and Learning holds teaching-related trainings and workshops on a monthly basis, there is no centralized instructional design support at UM.

UM CASE STUDY ONE: BIOLOGY I: INQUIRY INTO HUMAN LIFE

Biology I is a course for non-majors who seek to satisfy a general education lab science requirement. It is a course taught by multiple instructors (7), in multiple sections (16 in the Fall 2019 semester). In Fall 2019, 1054 students completed the course. Only one instructor of Biology I is a research-track faculty member, while the other 6 are instructional-track faculty.

In the Spring of 2010, the publisher's textbook package included an ebook and a digital learning platform. Although the faculty agreed that having an on-line system would help students study, at that time they decided not to adopt the online system, for formal course integration, although they did not object to students independently leveraging the digital learning platform as an ancillary learning tool.

In the Fall 2012 semester, the Biology I instructors switched publishers and textbooks to McGraw Hill's *Biology: The Essentials. First edition* by M. Hoefnagels. The decision to switch to a new textbook was based on the strength of Hoefnagels textbook, but instructors saw the additional benefit of the package's test bank, slides and other lecture resources, as well as an online homework system.

Initially, instructors did not require homework, and viewed the on-line system, LearnSmart, as a tool to help students study if they were willing to take the initiative to use LearnSmart. In the Fall 2015 semester, Biology I instructors

adopted the second edition of the Hoefnagels textbook. Alongside this change, some of the faculty added assignments from the LearnSmart online homework tool to the course requirements and have progressively increased the graded weight of these homework assignments. In Fall of 2017, half of the instructors also began to assign homework and practice activities from the adaptive add-on to the homework system. As a result of this change, the weight of the four exams has gone down, and more points now are assigned to low stake assignments.

In the decade between 2009 - 2019, both the average grade and median grade in Biology I rose significantly from a C- to a B-. In that same period, the overall ACT score for first year students taking the course rose from 22.7 to 24.4. If we determine college readiness by ACT scores, students taking Biology I have been increasingly prepared for the course in the last decade. In addition, the average GPA for upper-class students taking Biology I rose from a 2.5 to 2.7 between 2009 and 2019, also indicating a higher predictor of student success in that class. While it is impossible to determine if the improved rates of student success are due to improved readiness, a change in the points distribution for assessments, or deeper learning based on digital courseware usage, student feedback in focus groups indicates students perceive the courseware is effective for helping them learn:

I think [the courseware] really helps a lot because my instructor schedules the [learning modules] before she teaches it. Her doing that helps me learn what we are going to do next [in class].

[The courseware] actually makes me have to study less because I am doing the homework. In other classes where I don't have a lot of homework, I definitely have to study a lot before the test.

When you get certain questions wrong, [the courseware] goes back and tells you what you got wrong and why it is wrong and explains [the problem]. I think that is a lot more helpful than trying to find the answer [on my own] because I probably won't do it.

Students see benefits to use of the courseware in terms of increasing their preparedness for class, and building their confidence in test-taking by providing a realistic assessment of their knowledge and mastery of the material. However, the difficulty of the adaptive lessons that fail to provide feedback or guidance frustrates students. Many students also noted the high cost of the platform required for a one-semester course for non-majors. In the 2019-2020 academic year, purchase of the digital book and LearnSmart with the adaptive add-on, Connect, through the campus bookstore cost students \$140.00 for 24 months of access. This price was negotiated by faculty as a way to allow students to use the same access code for a second, related course, Biology II: The Environment, even though only 45% of students who successfully complete Biology I register for Biology II. Students who

purchased the Hoefnagels book and LearnSmart with Connect directly through McGraw Hill paid \$86.00 for six months of access.

UM CASE STUDY TWO: GENERAL CHEMISTRY PART 1

Chemistry I is part one of a two-part sequence of general chemistry required for majors in several degree pathways including engineering, computer science, and all health sciences. Chemistry I is taught by multiple instructors (7), in multiple sections (9 in the Fall 2019 semester). In the Fall of 2019, 747 of 921 students successfully completed the course, with 645 of those students going on to take Chemistry II. In any given semester, half of the faculty teaching general chemistry are research-track faculty and half are instructional-track faculty.

There is no coordination of Chemistry I outside of a common agreement among instructors to use the same textbook and to cover the same chapters during the semester to prepare students for Chemistry II. Faculty have full control over the content of their lectures, exams, homework, and practice activities. Faculty may choose to use or not use the digital courseware tied to the textbook. Faculty may choose how and when to assess their sections of Chemistry I, thus some sections may include graded homework, while others may not. Consequently, sections of the general chemistry sequence do not share the same homework, assessments, or lectures. However, all students who complete Chemistry I are required to take the American Chemical Society General Chemistry exam, which allows the department to measure student learning using a common assessment.

As textbook publishers began to include digital learning platforms in their course resources, Chemistry I faculty agreed that automated homework could help students better prepare for tests and could help reduce the number of students who came to ask questions about test prompts after each exam. In the Fall of 2009, the Chemistry I faculty adopted Pearson's Mastering Chemistry for the general chemistry sequence. By default, the faculty chose the accompanying textbook, *Chemistry: Structure and Properties* by Nivaldo J. Tro, since it was paired by Pearson with Mastering Chemistry. Every three years, the general chemistry instructors review the digital learning system and the textbook. They have renewed the current title and digital learning system three times since it was adopted in 2009.

The undergraduate student population grew 45% between 2006 and 2016, adding nearly 6,000 students to enrollments in general education classes. As classroom and instructor resources did not increase at that same rate, departments struggled to accommodate student enrollment requests. In response to this problem, the Department of Chemistry increased the minimum mathematics ACT score from 20 to 23, and eventually to the current threshold of 25. Raising math ACT requirements was a decision based on internal research regarding student performance in the general chemistry sequence.

In the decade between 2009 and 2019, both the average grade and median grade in Chemistry I rose from a C+ to a B-. In that same period, the minimum Math ACT score prerequisite for first year students taking the course was raised from 20 to 25. The rise in success grades (C and higher) also correlates with a decrease in failure grades (below C) during this same period, indicating an overall improvement in student learning. It is unclear whether student success increases are due to students being better prepared for the class, students learning more effectively on digital courseware, or both factors.

Despite these improvements in student success, student feedback on the implementation and use of the digital courseware has been mixed:

It is like taking two chemistry classes. It is like one is based on the book and the homework and one is based on lectures and the test.

I do like that [the courseware] gives you multiple tries and then, if you get it wrong, it will say “check on this” or hint you towards where you messed up.

I think it would be helpful, too, if the adaptive follow up was like truly adaptive. It doesn't take into account how you could ace one section of the homework and then just get like get three questions wrong that were similar but it is still going to test you on the stuff that you aced. It would be helpful if [the adaptive follow up] just focused on the stuff that you needed more help on.

A major problem for students is a lack of alignment between the content of lectures and high-stakes exams, and the content and assessments in the digital learning platform. This problem could be addressed through a collaborative course revision in which instructors align their sections together and align the course content of all sections with the content and assessments in the digital learning platform. Additionally, many students in the focus group, and particularly those students who are non-STEM majors, had concerns about the cost of the digital learning platform. In the 2019-2020 academic year, students paid \$243.00 for four-semester access to a digital version of the textbook, a loose-leaf text, and the digital learning platform. In 2019-2020c direct purchase through Pearson for a digital textbook and access to Mastering Chemistry for the same access period has been priced at \$119.00.

Between 2017 - 2019, UM faculty using digital learning platforms designated as adaptive were supported by vendor training sessions, debriefing sessions with the grant program manager and grant administrators from the Personalized Learning Consortium at the APLU, and through faculty development workshops focusing on student engagement, active learning, and learning analytics.

As faculty members become increasingly familiar with digital learning platforms, and heard student feedback regarding the value of these platforms as learning tools, they have become more willing to experiment with various products, and are making more informed choices when adopting these products for their courses. Some faculty members who teach Chemistry I have been replacing publisher textbooks with Open Educational Resources that are freely online for student use, and some faculty members have been assigning low-cost online homework systems in place of those offered by large textbook publishers.

COLORADO STATE UNIVERSITY CASE STUDIES

Colorado State University (CSU) is an R1 university located in Fort Collins, Colorado, sixty miles north of Denver. CSU serves an undergraduate population of over 26,000 students and a total student population of over 33,000.

The APLU grant required institutions to scale the use of adaptive courseware to 15-20% of general education enrollments; CSU's target numbers were 12,291-16,288 enrollments within courses using courseware. As seen in Table 1, scaling the adaptive courseware quickly gained momentum and CSU was just shy of hitting the grant target at the end of the second year with 11,336 enrollments. Upon completion of the grant, CSU anticipates that over 40,000 students will have taken courses redesigned due to the grant (Table 1).

Table 1

Courseware use Fall 2016-May 2020

<u>Academic Year</u>	<u>Course enrollments and sections by year</u>	<u>Cumulative enrollments and sections by year</u>
2019 – 2020*	7,898 in 68 sections	33,980 in 322 sections
2018 - 2019	14,746 in 121 sections	26,082 in 254 sections
2017 - 2018	8,212 in 82 sections	11,336 in 133 sections
2016-2017	3,124 in 51 sections	
*Includes Fall 2019 data only		

Faculty members participating in the grant redesigned their courses with the assistance of instructional designers to maximize the use and effectiveness of adaptive courseware. In concert with restructuring the courses to include courseware, instructional designers used this opportunity also to incorporate research-based teaching practices. Grant funding provided faculty with a salary stipend in exchange for their participation.

CSU divided the courseware integration into three components, including: strategic implementation of courseware, backward course design, and the incorporation of research-based teaching practices. A team of three instructional designers partnered with faculty members during the course redesign process and assisted in the selection and implementation of adaptive courseware and research-based teaching practices including active learning, high-impact practices and, in some cases, peer educators (Learning Assistants).

Following the process of backward design (Wiggins & McTighe, 2005), the faculty and instructional design team surveyed adaptive platforms to identify the appropriate courseware based on course objectives and the instructors' teaching goals. The team then identified research-based teaching practices and developed activities, assignments and feedback opportunities to incorporate in the course.

In addition to the course redesign consultations, the instructional design team organized the Faculty Collaboration Group (FCG), a faculty learning community focused on the implementation of adaptive courseware and research-based teaching practices. The FCG met five times during the academic year and provided faculty from across disciplines a forum to talk and learn about teaching. The FCG was also used as a recruiting forum for faculty who were interested but were not ready to commit to adopting adaptive courseware at that time.

Once faculty members were confident that they were going to receive support needed to take on the adaptive courseware adoption and course redesign effort, they joined the grant. Overall, faculty reported that they enjoyed having a space to share teaching challenges, successes, and strategies related to implementing adaptive courseware and research-based teaching practices.

USING DATA ANALYTICS DURING THE DASHBOARD CHALLENGE

Faculty members have numerous responsibilities and the addition of the courseware and research-based teaching practices proved time consuming. Finding the time to use the analytic dashboard was a challenge for many faculty members. In an effort to shine a spotlight on the courseware analytics, faculty members were challenged to use the courseware analytic dashboard for eight-weeks during the Dashboard Challenge. The Dashboard Challenge provided incentive to:

1. explore how the dashboard analytics could provide insight to student learning,
2. determine which content might need to be reviewed, and
3. identify students that may need nudges.

Faculty members recorded the time spent, the data report used, the intervention (changes to the class content or student outreach) as well as the results of the intervention. Faculty participants in the Dashboard Challenge were asked to share their experiences with other members of the FCG, a sharing activity which enticed more faculty to participate in the Dashboard Challenge the following semester. While this approach increased the use of the dashboard, in the long-term, regular use of the analytic dashboard was inconsistent.

CSU CASE STUDY ONE: BIOLOGY 1 FOR MAJORS

Biology 1 at CSU consists of a sequence of two introductory biology courses for majors taught by tenure and non-tenure track faculty. Specifically, LIFE 102 Attributes of Living Systems is the first-term of the sequence and enrolls 325 students per section with a total enrollment of over 2400 students each academic year while LIFE 103 Biology of Organisms is the second-term of the sequence and enrolls 225 students per section with over 700 students enrolled each academic year. The faculty team was in the midst of a book selection process when they were first approached with the grant opportunity to adopt adaptive courseware. With the exception of using the same textbook, faculty in the Biology 1 sequence have autonomy in their teaching practices; for this reason, taking a team approach to the course redesign was a unique opportunity. During the adaptive courseware redesign, the Biology 1 team completed the following:

- Added adaptive courseware as a *graded* component of the course (a requirement of the grant);
- Organized an activity and media resource library to share resources;
- Collaborated on the development of new in-class active learning activities;
- Incorporated research-based teaching practices including: multiple in-class formative assessment techniques, low-stakes warm-up exams within the first four-weeks of the class, and metacognitive post-exam wrappers encouraging students to reflect on text performance;
- Integrated Learning Assistants (one section per semester) to assist with active learning; and
- Reviewed the data analytic reports to make decisions related to content instruction or student outreach (as part of the Dashboard Challenge).

The redesigned version of Biology 1: semester 1 has been taught for three semesters whereas the redesigned version of Biology 1: semester 2 has been taught for two semesters. The redesign phases have allowed faculty members time to refine changes made to the course.

As indicated in Tables 2 and 3 below, there was an increase in students' success rates in most of the Biology 1 course sections taught by faculty members using the Adaptive/Active (adaptive courseware plus research-based teaching practices) format. The association of adaptive courseware/active learning on student success should be evaluated on a case-by-case basis. While Biology 1: semester 1 (with Instructor X941) shows seemingly different student success rates for adaptive/active and non-adaptive sections (85.5% versus 79.7%), these rates are statistically similar ($p\text{-value} > .05$). Despite the lack of statistical significance, the difference may warrant some practical significance: the 5.8 percentage point higher student success rate in the adaptive/active sections equates to an additional 17 students passing the course, relative to the non-adaptive sections.

Course Level Success by Adaptive Courseware/Active Learning Status

Tables 2 and 3 display the course success rates for each course and each instructor by adaptive courseware/active learning use. Comparisons are made at the instructor level to control for individual pedagogical differences. In Tables 2 and 3, bold text indicates instances when in which the success rates for adaptive/active sections are at least 1 percentage point (PP) higher than the non-adaptive sections. Additionally, the Pearson Chi-square $p\text{-value}$ for each course/instructor pair is displayed; success rates with statistically significant differences ($p\text{-value} \leq .05$) are marked with an asterisk (*).

Table 2

Adaptive/Active and Non-adaptive Student Success Outcomes in Biology 1: semester 1 by Instructor

<u>Instructor</u>	<u>Headcount</u>		<u>A, B, C, or S</u>		PP <u>difference</u>	Pearson Chi- <u>square</u>
	<u>Non- adaptive</u>	<u>Adaptive/ Active</u>	<u>Non- adaptive</u>	<u>Adaptive/ Active</u>		
W394	748	749	77.8%*	82.0%*	4.2	0.04
L298	610	303	75.1%	74.9%	-0.2	0.96
R419	330	299	67.3%*	79.6%*	12.3	<0.01
X941	305	303	79.7%	85.5%	5.8	0.06
* Statistically significantly different at $p \leq .05$ Bold text indicates instances when the success rates for adaptive/active sections are at least 1 percentage point (PP) higher than the non-adaptive sections.						

Table 3

Adaptive/Active and Non-adaptive Student Success Outcomes in Biology 1: semester 2 by Instructor

<u>Instructor</u>	<u>Headcount</u>		<u>A, B, C, or S</u>		PP <u>difference</u>	Pearson Chi- <u>square</u>
	<u>Non- adaptive</u>	<u>Adaptive/ Active</u>	<u>Non- adaptive</u>	<u>Adaptive/ Active</u>		
W394	275	271	88.7%	90.0%	1.3	0.62
R214	227	235	70.5%	74.0%	3.6	0.39
Bold text indicates instances when the success rates for adaptive/active sections are at least 1 percentage point (PP) higher than the non-adaptive sections.						

CSU CASE STUDY TWO: GENERAL CHEMISTRY FOR SCIENCE MAJORS

General Chemistry at CSU consists of a sequence of two introductory chemistry courses for science majors taught by non-tenure track faculty. Specifically, CHEM 111, General Chemistry I, enrolls 200+ students per section with an enrollment of approximately 2000 students each academic year while CHEM 113 General Chemistry II enrolls 200+ students per section and approximately 1200 students annually. Prior to joining the grant, the General Chemistry faculty were using the ALEKS platform in conjunction with an OpenStax book. In Spring 2019, the Chemistry team joined the grant and started using a textbook associated with LearnSmart; they continued to use ALEKS, such that students were using two different courseware options to address course concepts. The redesigned version of General Chemistry I has been taught for two semesters, allowing faculty members time to adjust the changes they have made to the course, whereas the redesigned General Chemistry II course has only been taught once.

While the General Chemistry I faculty used a common syllabus, instructors used a variety of teaching practices in the classroom. During the redesign, the Chemistry faculty took a team approach and shared materials and resources developed during the process. During the adaptive courseware redesign, the Chemistry team:

- Added LearnSmart as a *graded* component of the course (a requirement of the grant);
- Organized an activity and media resource library to share resources;
- Collaborated on the development of new in-class active learning activities including think-ink-pair-share, iClicker predictions, and instructor lab demonstrations;
- Incorporated research-based teaching practices including:
 - 1) identifying and sharing learning outcomes with students for each class session,
 - 2) using multiple in-class formative assessment techniques, and
 - 3) explicitly sharing common misconceptions and student errors with students;
- Used data analytic reports to make decisions related to content instruction or student outreach (as part of the Dashboard Challenge); and
- Piloted the use of Learning Assistants to assist with active learning in Spring 2020.

Student Perception Survey Results

Student perception surveys were administered to students at the end of the semester. In Fall 2019, over 2000 students responded to the eleven question survey. The qualitative data has been sorted by course (Tables 4 through 7) whereas the student comments have been combined.

Table 4

Student Survey Results in General Chemistry I by Platform

	<u>No</u>	<u>Somewhat</u>	<u>Yes</u>
LearnSmart was easy to use	7.2%	36.5%	56.3%
LearnSmart had technical problems that prevented me from completing my work	54.4%	27.6%	18.0%
LearnSmart helped me learn	11.9%	46.9%	41.9%
ALEKS was easy to use	14.2%	37.2%	48.6%
ALEKS had technical problems that prevented me from completing my work	50.6%	29.1%	20.3%
ALEKS helped me learn	8.0%	26.4%	65.7%

As indicated in Tables 4 and 5, students in the General Chemistry courses felt that both the LearnSmart and ALEKS platforms were easy or somewhat easy to use. About half of the students experienced technical problems with the two systems that may have made it difficult for them to complete the assigned work. Overall, more than half of the students indicated that ALEKS helped them learn.

Table 5

Student Survey Results in General Chemistry II by Platform

	<u>No</u>	<u>Somewhat</u>	<u>Yes</u>
LearnSmart was easy to use	12.1%	22.4%	65.5%
LearnSmart had technical problems that prevented me from completing my work	67.5%	18.2%	14.3%
LearnSmart helped me learn	26.0%	47.6%	26.7%
ALEKS was easy to use	17.7%	36.2%	46.2%
ALEKS had technical problems that prevented me from completing my work	52.5%	26.2%	21.3%
ALEKS helped me learn	14.1%	27.7%	58.2%

As indicated in Table 6, over 70% of students in both biology courses felt that the courseware was easy to use. Over 72% of students in both biology courses did *not* experience technical problems that prevented them from completing their work. Finally, as shown in Table 7, over 70 % of students in Biology 1, semester 2 and 90% of students in Biology 1, semester 1 felt that the platform was somewhat helpful to their learning.

Even though all four courses used the LearnSmart courseware, student responses to “ease of use,” “experience with technical problems,” varied greatly. Student responses to “helped me learn” were fairly consistent between the first course in a series (General Chemistry I and Biology 1, semester 1) and the subsequent course (General Chemistry II and Biology 1, semester 2). In General Chemistry and Biology 1 course series, the same textbook (and platform) were used for both courses within each series. Therefore, by the second course in a series, students may not have needed the same level of support they had needed during the initial course.

Table 6

Student Survey Results in Biology 1: Semester 1 by Platform

	<u>No</u>	<u>Somewhat</u>	<u>Yes</u>
LearnSmart was easy to use	2.8%	19.9%	77.0%
LearnSmart had technical problems that prevented me from completing my work	72.7%	19.6%	7.8%
LearnSmart helped me learn	8.5%	45.7%	45.7%

Table 7

Student Survey Results in Biology 1: Semester 2 by Platform

	<u>No</u>	<u>Somewhat</u>	<u>Yes</u>
LearnSmart was easy to use	0%	28.6%	71.4%
LearnSmart had technical problems that prevented me from completing my work	73.5%	16.3%	10.2%
LearnSmart helped me learn	22.5%	55.1%	22.5%

Open-Ended Student Feedback

The last question of the survey was “*Thank you for sharing your thoughts related to adaptive courseware. What should we know about your experience with [platform name] that we did not ask you?*”. This question prompted a variety of open-ended responses. While some students liked the instant feedback feature designed to encourage students to complete work they have not mastered, other students found the features to be frustrating.

Student Comments for Faculty

It was a good tool that ensured that I learned and interacted with the information I was given in the textbook for the week. In other words, it kept me accountable in my learning.

The courseware was easy and fun to use. I used it mostly as a review for me as I knew most of the material already.

I liked being able to test my learning and practice even after I submitted the assignment.

I really liked the instant feedback I was able to receive when answering the homework questions.

Student Recommendations for Vendors

You should get rid of the little person who pops up every minute telling me to read more.

It seems that this program allows professors to assign more homework than they normally would.

Many [sic] of the time the software is finicky and will not let you continue due to a misspelling even if you know the material. It is extremely frustrating.

Disliked when the homework quizzes told me to read more. It just further frustrated me when I was doing poorly.

I think it's a good tool but I would REALLY love a way to turn off the little speech bubble that tells me when to answer questions and when I should read more. The software glitches a lot but that's to be expected.

PORTLAND STATE UNIVERSITY CASE STUDIES

Portland State University is a public, urban university located in the heart of downtown Portland, Oregon. PSU has seven colleges, 211 undergraduate and graduate degree programs, approximately 25,000 students and 1800 research and instructional faculty. The University was interested in participating in the APLU grant program to pilot the use of adaptive learning platforms for several reasons. As Oregon's most diverse campus, Portland State is home to many students from underrepresented backgrounds. Nearly half of PSU students are the first in their families to attend college, approximately 43% are students of color, and 70% of all students receive financial aid. In addition to coursework responsibilities, many students work significant hours, and come to introductory courses with various levels of preparation. Student feedback indicates that the cost of course materials is also becoming a stressor, and students with significant work and/or family obligations outside of class find it more difficult to get timely assistance with homework than their peers with fewer outside responsibilities.

The adaptive learning project was administered and supported through PSU's Office of Academic Innovation (OAI). OAI is an educational development office of 24 staff, combining expertise areas of postsecondary education, curriculum development, instructional technologies, instructional design, digital learning, high impact practices, and assessment. OAI's mission is to "promote and support effective student learning at PSU by building sustainable instructional capability, collaborating with educators across campus to come up with innovative instructional solutions, and fostering creative communities committed to teaching and learning". OAI sent a call for participation to the campus, titling the project "Active and Adaptive," to reinforce the goal of course design that would incorporate active learning strategies as a result of students having mastered foundational concepts prior to attending class.

Each participating faculty member in the adaptive project partnered with an OAI team. A project manager was responsible for coordination management across the various course projects. The partnerships with OAI often made a difference in how challenges were addressed and successes built upon. For example, assessment staff shared timely results from student experience surveys with faculty members, who could meet to discuss any appropriate modifications with an OAI consultant who was already familiar with (and had helped to design) the course. This was especially important for faculty members who had less experience with just-in-time modifications to course structure based on immediate student learning data, as will be discussed below.

PSU CASE STUDY ONE: BIOLOGY FOR NON-MAJORS

In Winter quarter of 2017, Biology for non-majors at Portland State joined the active and adaptive grant at Portland State University (PSU) with the goal to make learning more personal for students in large enrollment courses (Dziuban, Moskal, Johnson, & Evans, 2017). A team of three -- professor, user experience (UX) designer, software representative -- began collaborating over a period of 12 weeks to build the first of a series of three Introductory to Biology courses for non-majors. This process included the development of resources for onboarding 500+ students for the academic year to the new adaptive learning platform, ingesting and building content into the adaptive platform, and adding digital resources such as images, charts, and videos and interactive quizzes. Overall, the process was informed by research which indicates that students benefit from technology when they use it frequently and in a variety of ways (Kuh & Hu, 2001; Freeman et al., 2014). The primary feedback from the initial course pilot in Spring quarter of 2017 focused mainly on the need for alignment of the open educational resource (OER) materials to the faculty member's lecture and in class activities (Geith & Vignare, 2008).

For summer of 2017, a graduate research assistant was hired to develop and work with the instructor with redesign of the Introductory to Biology course to update and align content. Throughout the full Fall 2017- Spring 2018 academic, students used the adaptive platform in Biology and were introduced to more active learning during in class sessions (Freeman et al., 2014). To support a new active and adaptive teaching modality, the Biology professor reviewed daily and weekly student progress reports in the adaptive system and adjusted her lectures and in-class clicker questions based on areas in which the system indicated students needed extra review. Active learning was organized as in class group work wherein students were asked to address problem-solving tasks in class (Freeman et al., 2014; Kerns, 2019). Continuously throughout the first-year deployment, extensive student feedback was collected, reviewed, evaluated and used to inform future decisions regarding the design and the structure of the course. Now in the third year of delivery, the adaptive Biology sections are fully self-sustained by the faculty member without support from an internal team at PSU.

PSU CASE STUDY TWO: GENERAL PHYSICS

The Physics department at Portland State University (PSU) has long struggled with the challenge of teaching large classes of diverse students. Coming from a variety of socio-economic and educational backgrounds, students begin the sequence with a largely disparate amount of prerequisite knowledge and variable levels of motivation for learning the material. Recognizing this issue, in the summer of 2018, the Physics team at PSU began the process of redesigning a three-course series of PH 201-203, known as General Physics, to create a resource that would support the students' long-term success without burdening them with the high cost of the homework platforms being used at the time.

After a review of a variety of adaptive learning platforms, the Physics team chose to develop in CogBooks, a platform that would give students the opportunity to review content relevant to the class sessions, but also would provide students the chance to engage with the concepts through multiple media integrations, including videos, simulations and problem solving. CogBooks also provided students with the agency to move through the materials as they chose, while still offering recommended paths based on students' self-assessed understanding of the topic being presented. Creating materials that would not be cost-prohibitive to students was also key; instead of paying out of pocket for a textbook, video platform, clicker, and a separate homework platform (which totaled just over \$250 per year), the Physics team aimed to create a tool that would be home to all of their course content and homework, including open source lessons, videos, and simulations authored or adapted by the instructor; these curricular materials were provided to the student at a significantly lower cost.

With a backward design approach in mind (Wiggins & McTighe, 2005), the Physics team first identified the learning objectives for each of the topics to be covered in the courses. Scaffolded activities were then designed to provide students with learning paths that offered opportunities for further exploration of the concepts. To support an active classroom, the team designed the materials such that students would be required to complete a portion of the content and activities on a given topic before coming to the lecture covering that topic. This pre-class exposure to the content and activities related to a topic would help students familiarize themselves with the topic of the subsequent lecture and provide them with questions that would help the students assess their own understanding. Based on their performance, students could then opt to review additional materials that expanded on the topic in an attempt to better prepare themselves for each upcoming class session. In this way, students could come to class with a better understanding of the topic, allowing for more targeted discussions and the opportunity for students to participate in group activities, leading to an engaged classroom centered on active teaching techniques.

The process of redesigning this course sequence began with identifying open source resources that could be used to create a cohesive and well-aligned curriculum. These resources were then adapted and organized to align with the instructor's course outline. Each of the three courses were developed in the term prior to its delivery with the support of the main instructor, an instructional designer, a UX designer and two former Physics students. During a twelve-week design cycle, content and questions were created, tested and then revised by the team to prepare for delivery. The team also reviewed student feedback at regular intervals to inform changes made to future development. After the first year of delivery, a more extensive review of the student data and comments informed further updates and changes to the materials. Now in the second year of delivery, the Physics team is continuing this iterative design approach, further refining the materials and how they are being used.

STUDENT SURVEY DATA RESULTS

The 'Active and Adaptive Implementation Student Survey' was created in an effort to collect student feedback on the impact adaptive courseware had on their overall learning in active and adaptive courses. The student survey comprised 14 Likert scale questions and two open-ended questions. Table 8 and Table 9 provide student responses for seven of the 14 rating scale questions for biology and physics active and adaptive courses conducted from Fall 2018 to Fall 2019 across four academic quarters. The seven selected survey questions represented in Table 8 and Table 9 provide student ratings regarding how CogBooks impacted student learning for the course as well as students' perceptions of the connections between the content in the courseware and class activities.

Table 8

Student Responses on Active and Adaptive Implementation Survey for Biology Courses from Fall 2018 – Fall 2019 (1 = Strongly Agree; 6 = Not Applicable (N/A))

	<i>Percentage of Total Responses per Item (n=206)</i>					
<i>Statement</i>	<i>Strongly Agree</i>	<i>Agree</i>	<i>Neither Agree nor Disagree</i>	<i>Disagree</i>	<i>Strongly Disagree</i>	<i>N/A</i>
1. CogBooks helped me prepare for class.	47.74	39.50	5.29	5.54	2.21	0.00
2. CogBooks helped me prepare for quizzes and exams.	45.52	38.23	9.03	5.90	1.10	0.00
3. Feedback in CogBooks helped me stay on track.	37.08	30.39	21.26	8.61	1.49	1.43
4. CogBooks helped me to identify what I am struggling with.	44.04	30.94	16.02	6.94	2.04	0.50
5. Using CogBooks increased my confidence in my own learning.	39.05	25.61	25.60	7.31	2.69	0.00
6. The work I do in CogBooks and class activities were connected.	47.84	41.44	5.56	3.04	1.20	0.70
7. I would take a course in the future that uses CogBooks.	42.17	37.32	15.13	4.31	1.10	0.00

Table 9

Student Responses on Active and Adaptive Implementation Survey for Physics Courses from Fall 2018 – Fall 2019 (1 = Strongly Agree; 6 = Not Applicable (N/A))

		<i>Percentage of Total Responses per Item (n=218)</i>				
<i>Statement</i>	<i>Strongly Agree</i>	<i>Agree</i>	<i>Neither Agree nor Disagree</i>	<i>Disagree</i>	<i>Strongly Disagree</i>	<i>N/A</i>
1. CogBooks helped me prepare for class.	30.56	42.95	9.56	10.42	6.74	0.00
2. CogBooks helped me prepare for quizzes and exams.	34.06	40.84	10.52	10.70	3.67	0.00
3. Feedback in CogBooks helped me stay on track.	20.53	28.19	22.04	15.4	12.75	1.09
4. CogBooks helped me to identify what I am struggling with.	21.35	29.61	17.53	19.07	12.10	0.34
5. Using CogBooks increased my confidence in my own learning.	20.35	28.67	19.68	18.30	12.76	0.00
6. The work I do in CogBooks and class activities were connected.	35.97	53.48	4.23	4.25	0.75	0.35
7. I would take a course in the future that uses CogBooks.	22.43	31.24	18.14	12.42	14.60	0.40

An examination of student survey responses to prompts regarding the impact of CogBooks to their overall learning in the biology active and adaptive courses (Table 8), students selected statement 6, “The work I do in CogBooks platform and class activities were connected” as the highest rated ‘*Strongly Agree*’ item at 47.84%. Conversely, students selected survey statement 3, “Feedback in CogBooks helped me stay on track” as the lowest rated ‘*Strongly Agree*’ item at 37.08%. Analysis of student survey responses regarding the impact of CogBooks to their overall learning in the physics active and adaptive courses (Table 9) reveals that students also selected statement 6, “The work I do in CogBooks and classroom activities were connected” as the highest rated ‘*Strongly Agree*’ item at 35.97% and statement 5, “Using CogBooks increased my confidence in my own learning” as the lowest rated ‘*Strongly Agree*’ item at 20.35%.

In addition to the rating scale survey questions outlined in Table 8 and Table 9, students in the adaptive courses were also asked the following open-ended questions in the active and adaptive implementation survey:

1. What aspects of the course, if any, increased your learning?
2. What aspects of the course, if any, were barriers to your learning?

Thematic analysis of repeating ideas raised by the biology and physics course students who responded to these two open-ended questions revealed the following themes:

Self-paced learning. Students reported that, through the use of CogBooks, they were able to go through content at their own pace, get feedback in real time, and continuously practice concepts for understanding and mastery. As stated by a student in an active and adaptive biology course, “Mostly [I valued] the practice of reading and answering questions, especially when one that I got wrong before pops up again, it feels good to get a second chance at the question, also, being able to have the text on the side of the question with no point-penalty decreases any possibility of test anxiety.”

Platform navigation and depth. Students in the biology and physics active and adaptive courses reported that CogBooks provided helpful resources, robust knowledge checks, and visual tracking of their process through engaging modules. A student in one of the active and adaptive physics courses stated, “CogBooks is the best tool for me in learning the material of this course.” However, platform navigation and complexity were areas about which students reported mixed sentiments, specifically, concerns with technical glitches and difficulty navigating through the platform interface. As stated by a student, “CogBooks at times was difficult to work with.” Another student stated, “CogBooks did not show work and answers for questions you get wrong.”

Classroom and adaptive learning alignment. Students in the biology and physics active and adaptive courses reported that the active and adaptive alignment provided an opportunity to work through the course material within CogBooks at their own paces and solidified concepts through active learning in the classroom. A student in one of the active and adaptive biology courses stated, “Doing the CogBook exercises before class helped me get ready for the class and have a good understanding of what we are about to learn that day.” This was also an area in which some students reported mixed sentiments, specifically, a slight variance in when the materials were provided. As stated by one student, “CogBooks activities were very well connected to class in content, but it would tend to be ahead of the class by about a class period (because we would have to do it before the lecture, so in a sense, we would have to teach ourselves how to do those types of problems, in order to do the homework, before we learned how in class).”

Overall, the student survey responses provided the active and adaptive research team at Portland State University with an opportunity to examine potential impacts of the integration of adaptive courseware on student learning both in the classroom and through self-paced learning.

UNIVERSITY OF CENTRAL FLORIDA CASE STUDIES

The University of Central Florida (UCF) is an R1 public research institution within the State University System of Florida located in metropolitan Orlando. With 13 colleges and more than a dozen locations, UCF offers over 220-degree programs to over 69,000 students. Almost half of the student population are minorities, and UCF has been recognized as a Hispanic-Serving Institution. In the 2018-19 academic year, nearly half (47.4%) of the total university Student Credit Hours (SCH) were delivered online or blended, and nearly one-third (31.4%) were fully online. In that same academic year, 85.1% of all students took at least one online or blended course. Both measures (SCH and headcount) have grown steadily in recent years.

The Center for Distributed Learning (CDL) is a service organization dedicated to supporting online and blended learning for UCF faculty and students. In addition to offering technical support for both faculty and students, CDL also offers faculty instructional support services such as instructional design and professional development as well as multimedia services including video, graphics, and captioning support. Specific to this study, within the CDL instructional design team there are a group of instructional designers who are dedicated to assisting faculty members with the design and development of courses using adaptive learning systems. Also housed within CDL is the Pegasus Innovation Lab (iLab), which serves as a project management office for institutional level initiatives that

foster innovation in digital learning. As such, the iLab served as the project lead for this grant project; two instructional designers who specialize in adaptive learning were assigned to work directly with the instructors.

Based on UCF's historical success with online, blended, and adaptive courses, the university's Board of Trustees also made a strategic investment in a Digital Learning Course Redesign Initiative. The goal of this initiative was to impact student learning by increasing successful course completion (reduced DFW rates), particularly in General Education Program (GEP) & STEM courses, and to improve First Time in College (FTIC) & Transfer student persistence through a strategic course redesign process that leverages the benefits of online, blended, adaptive, and active learning. The courses described in the following case studies were included in the over 100 course redesign projects, of which almost half were focused on adaptive learning implementations.

UCF CASE STUDY ONE: BIOLOGY FOR MAJORS

Biology I is a major's biology course, but typically about 85 percent of the students are majors from other science disciplines such as actuarial science, computer science, sports and exercise science, psychology, and nursing. Normally Biology I is offered in five to seven sections a year with 450 students per section, which results in an annual population of 7,000 - 8,000 students. The venue is a fixed seat auditorium. Due to TA and UTA staffing constraints, active learning can be supported only every other week, but there is a desire to increase that frequency.

The course was redesigned as a blended class using the Realizeit adaptive platform as the online content delivery method to allow for active learning in the classroom meetings based on best practices established in pilot courses (Chen, Bastedo, Kirkley, Stull, & Tojo, 2017). The online instructional content was built from the ground up with every module using instructor authored content and OER resources. Eleven of the fourteen chapters are taught using the adaptive platform. The initial three modules in the course involve new and remedial information to allow for unification of skills within the class. As one example, acids and bases, properties of water and pH/pOH problems are taught within the initial three course modules.

The modules from Proteins (Macromolecules) through the end of the semester material present only new content. Case studies are utilized to help students master the material and foster increased engagement (Hinkle & Moskal, 2018). Light Board videos are provided to highlight more complex problem-solving techniques. Although traditional types of questions are also included in each module, many compound and varied questions are utilized. Due to the number of students, most of the questions are randomized and contain a wide range of variables. This allows students to collaborate, yet still learn the content without compromising question banks and assessment outcomes.

Students are expected to read the e-book, do the adaptive modules in Realizeit, and then come to class for active learning exercises every other week, followed by an in-lecture quiz assessment to determine their progress. The students have confided that using the adaptive platform is such a complete help to them that they rarely need to read the e-book now.

When students flag a question, the instructor uses that input as an opportunity to initiate a virtual chat with the student to determine the depth of the student's understanding. The information from flagged questions allows the instructor and TAs to see exactly what students do not understand regarding any concept and to analyze the precise way in which the student has arrived at a misunderstanding. This information can then be utilized to correct any misconceptions. From these analytics the instructor also can see trends within the entire class.

Over time, UCF course designers have progressed in using more complex functions of the Realizeit adaptive system, such as alternative learning pathway opportunities. These complex functions now support three occasions during the semester when students are learning several topics online using solely the adaptive platform and, as such, now these topics are never covered in lecture.

After the course was first taught in the new format, an "Introduction to the Realizeit Adaptive Platform" module was added to better acquaint students with the many opportunities the software affords them to learn in different ways. As a result, students have requested that adaptive modules remain accessible to them after the due date for active learning has passed, so that they may use these modules as a study tool for exams and can refer to them throughout the semester.

The use of information from student reported emojis in Realizeit has also been incorporated into the course redesign. That information has been used successfully to detect students who are having academic challenges. Based on the students' reported affective emojis, the instructor and TAs invite the students to get help via email or in person. One future goal will be to place TAs in the adaptive system, in real time, to work with the students.

Institutional level student success, withdrawal, and satisfaction data have been collected for each course. Biology I results are reported in Table 10. Student success is defined as a final course grade of A, B, or C. Success and withdrawal data is reported as a percentage of the total class enrollment. Ideally after a course redesign, the data will reveal a desired increase in student success and a desirable decrease in withdrawal rates. Student satisfaction is measured by the overall course ratings students submit on course evaluations, reported as the class mean on a scale of 1-5 where 1 is poor and 5 is excellent.

Table 10

Biology I: Comparison of Student Success, Withdrawal, and Satisfaction in Redesigned Spring 2019 Course Compared to Last Section Taught Prior to Redesign

	<i>Number of Students (n=766)</i>		
<i>Measurement</i>	<i>Spring 2019</i>	<i>Previous Course Offering</i>	<i>Change</i>
Student Success (Final Grade A, B, or C)	84%	73%	+11%
Student Withdrawal	2%	4%	-2%
Student Satisfaction (End of Course Evaluation on a scale of 1-5)	4.55	4.22	+0.33

After fully implementing the redesigned course with online adaptive learning and active learning in the classroom, student success as measured by a final course grade of A, B, or C increased 11 percentage points from 73% prior to redesign to 84% in Spring 2019. The withdrawal rate decreased from 4% to 2%, and student satisfaction as measured on the end of course evaluations increased significantly.

Students were also asked to complete an anonymous feedback survey at the end of the course. Table 11 summarizes the quantitative feedback from 110 respondents.

Table 11

Student Responses on Personalized Adaptive Learning Anonymous Survey for Biology I

		<i>Percentage of Total Responses per Item (n=110)</i>				
<i>Statement</i>	<i>Strongly Agree</i>	<i>Agree</i>	<i>Neither Agree nor Disagree</i>	<i>Disagree</i>	<i>Strongly Disagree</i>	<i>Not sure or No Answer</i>
1. Overall, Realizeit helped me learn the course material better than not having Realizeit.	21%	51%	16%	3%	2%	7%
2. Realizeit provided me with the necessary feedback to help me stay on track with the course objectives.	6%	51%	25%	6%	1%	10%
3. The instructions in Realizeit were clear.	12%	54%	21%	2%	1%	11%
4. The ability levels reported by Realizeit were accurate.	9%	52%	18%	6%	1%	14%
5. Realizeit became personalized to me over time.	12%	34%	29%	5%	3%	18%
6. The grading accurately reflected my knowledge.	12%	55%	16%	6%	1%	10%
7. The Realizeit assessment exercises were effective in measuring my learning.	11%	52%	21%	4%	2%	11%
8. Realizeit increased my engagement with the course content.	15%	48%	19%	5%	2%	11%
9. Realizeit was easy for me to use.	29%	45%	15%	2%	1%	9%
10. Given a choice, I would take another course using Realizeit.	20%	40%	22%	5%	1%	12%

Overall, the student feedback was very positive. In particular, it should be noted that 72% of respondents agreed or strongly agreed that the adaptive delivery helped them learn the course material better than learning without the adaptive platform. Also, only 6% reported that they disagreed or strongly disagreed with the statement “Given a choice, I would take another course using Realizeit.” When students were asked what they liked most about the adaptive platform, a clear theme around ease of use emerged. This theme was reinforced by students’ responses to item 9 shown in Table 11; 74% of respondents agreed or strongly agreed that the adaptive platform was easy to use. Several open-ended responses also related to the personalized experience:

I like that it covers the content and it is personalized to my learning ability and it focuses on what I need to go over rather than going over everything.
It went back and taught me if I missed a question.
It gave second chances.

Another student comment reads as follows: “*It gave me a great way to practice problems before an exam.*” This premise was reinforced anecdotally by the instructor. Students’ responses to open-ended questions also revealed a theme: Many students wanted more practice problems. This theme reflects students’ levels of engagement and the value they see in using this adaptive system.

UCF CASE STUDY TWO: SPANISH TWO-COURSE SEQUENCE

Two instructors collaborated on the redesign of Elementary Spanish Language & Civilization I (Spanish I) and Elementary Spanish Language & Civilization II (Spanish II) to be delivered fully online with adaptive learning in Realizeit using all Open Educational Resources (OER). This course redesign allows students to progress through the material at a pace and level that is comfortable for them and that reflects their actual prior knowledge. Although Spanish I assumes no knowledge of Spanish, the reality is that many students have some prior knowledge of the language; the reasons for this are varied: they took Spanish in school at some point before entering UCF, they live in an area where Spanish is spoken (Miami, for example), and/or they have family members who speak Spanish. Adaptive Learning using Realizeit allows students to create their own learning path and concentrate on the concepts for which they need more knowledge and practice. In the past, students have not been stimulated by publisher content or practice activities. Using adaptive learning and OER content in their course redesign allowed the instructors to design the courses to be more personal, more appealing, and more meaningful to students. OER-infused adaptive learning allowed the instructors to highlight real world application of the material they were presenting to the students. Students entering the course had repeatedly stated the goal of applying what they learned in the course to their lives in the real world, to use Spanish in a real-world context.

Using an adaptive learning tool allows instructors to monitor student progress more closely, and to supplement where necessary. Instructors can guide individuals more successfully based on the results set forth in the Realizeit adaptive platform and can help students with strategies for success. Before adopting the use of adaptive courseware, it had been possible, but far more difficult for Spanish instructors to determine each student's individual strengths and weaknesses, and to assess the strength and weaknesses of the class population, as a whole. In the first semester during which the redesigned course was implemented, students completed (and repeated) the Realizeit sections for each lesson even though redoing the work was not required or connected to a specific or separate percentage of the grade, and these students repeatedly reported how helpful and intuitive they found this learning approach.

There is often a struggle to connect with students in online courses, even when instructors are using all the online teaching and learning best practices and strategies they've learned. A tool like Realizeit helps them identify pockets of need early on, leading instructors to attend to their classes in a way that is much more proactive and effective. There are also features of the adaptive platform that allow students to self-report via emojis how they are feeling as they progress through the material and course. This is valuable because the use of emojis allows instructors to identify potential similarities among students' self-reported moods. Knowledge of mood trends gives an instructor the opportunity to address student issues personally or to contact students individually to discern why they might be feeling a certain way.

Students often view Spanish language courses as just "something to get through" since the courses meet language requirements. Many students struggle with the online delivery mode, either because it is new to them or because the publisher content and/or platform is not user friendly or has technical problems and glitches that are frustrating. These obstacles negatively impact student success, satisfaction, and retention. They also make it challenging for the instructor to encourage students to declare a major or minor in Spanish language studies. Another factor that impacts student attitudes toward these courses is the cost of the textbook and publisher LMS. Previously, students were spending about \$275.00 for the textbook and LMS package. Because the Realizeit license has been paid by the university, students have not been required to spend any money.

Institutional level student success, withdrawal, and satisfaction data were collected for each course; Spanish I results are reported in Table 12 and Spanish II results are reported in Table 13. Student success is defined as a final course grade of A, B, or C. Success and withdrawal data are reported as a percentage of the total class enrollment; ideally after a redesign and increase in student success and decrease in withdrawal would be desirable. Student satisfaction is measured by the overall course rating on the student end of course evaluation, reported as the class mean on a scale of 1-5 where 1 is poor and 5 is excellent.

Table 12

Spanish I: Comparison of Student Success, Withdrawal, and Satisfaction in Redesigned Spring 2019 Course Compared to Last Section Taught Prior to Redesign

	<i>Number of Students (n=67)</i>		
<i>Measurement</i>	<i>Spring 2019</i>	<i>Previous Course Offering</i>	<i>Change</i>
Student Success (Final Grade A, B, or C)	91%	68%	+23%
Student Withdrawal	3%	10%	-7%
Student Satisfaction (End of Course Evaluation on a scale of 1-5)	4.55	4.41	+0.14

Table 13

Spanish II: Comparison of Student Success, Withdrawal, and Satisfaction in Redesigned Spring 2019 Course Compared to Last Section Taught Prior to Redesign

	<i>Number of Students (n=91)</i>		
<i>Measurement</i>	<i>Spring 2019</i>	<i>Previous Course Offering</i>	<i>Change</i>
Student Success (Final Grade A, B, or C)	87%	65%	+22%
Student Withdrawal	7%	20%	-13%
Student Satisfaction (End of Course Evaluation on a scale of 1-5)	4.46	4.00	+0.46

As reported in Table 12, the redesigned Spanish I course with adaptive instruction was first delivered to 67 students in Spring 2019 and the percentage of students who successfully passed the course with an A, B, or C increased by 23% over the previous term during which the course had been taught by the same instructor. The withdrawal rate decreased from 10% to 3%. The student satisfaction measure on the end-of-course evaluation for the course taught the previous semester already had been relatively high at 4.41, but student satisfaction also increased after the course redesign.

The redesigned Spanish II course yielded similar outcomes. The student success rate increased 22% over the previous term taught during which the course had been taught by the same instructor, and the withdrawal rate went down 13 percentage points. Most noteworthy is the student satisfaction rating from the end of course evaluations which increased significantly from 4.00 to 4.46 on a scale of 1-5.

These results caught the attention of both administrators and colleagues within the academic departments, which led to conversations about scaling this redesign, program-wide, across 96 Spanish language course sections and 3,000+ students per year. The two original instructors will continue to revise and enhance the current redesigned courses with student course assistants and two additional instructors each semester until a refined active and adaptive course design is rolled out across the entire program. In parallel, instructors who teach other languages including Italian, German, French, and Portuguese plan to use the Spanish course designs as a model for building adaptive instruction in their programs.

DISCUSSION AND FUTURE DIRECTIONS

This article sought to address two questions across multiple adaptive learning cases studies: What do students perceive are the benefits to the implementation of adaptive courseware? How does the deliberate alignment between adaptive courseware and course organization and structure impact student experience?

BENEFITS

As can be seen from the case study examples, there were some early indicators of increased student success, particularly as measured by student pass rate and course completion. Student feedback indicated the perceived benefits of accountability, real-time feedback, and opportunities for frequent knowledge testing. Students also appreciated the additional preparation for classes, preparation for exams, and the ability for adaptive courseware to identify specific areas of strength and areas needing more work or assistance.

BARRIERS

Although student feedback on perceived benefits was positive across case studies overall, data also revealed barriers to effective incorporation of adaptive instruction into courses. For example, students in several courses desired more targeted real-time feedback and guidance connected to adaptive lessons, particularly when encountering roadblocks, or lack of progression with course concepts. Students also reported some technical challenges, including issues with navigating some components of the adaptive courseware. For some students, the costs associated with platforms were challenging, while for others, the time associated with completing adaptive lessons was a barrier to completing all assigned sections. Two primary adaptive learning experiences were expressed *both* as a benefit and barrier: real-time feedback with frequent knowledge checks, and the perceived alignment, or integration of adaptive courseware into course organization and instruction, to be discussed further below.

FEEDBACK AND KNOWLEDGE CHECKS

Knowledge checks and feedback built into adaptive courseware may enhance the opportunity for ‘practice at retrieval’ (Halpern & Hakel, 2003; Karpicke & Blunt, 2011), a process in which students repeatedly access and apply information as part of the learning experience, thus reinforcing and deepening comprehension and retention of material. Therefore, when students were not progressing in a given area, more targeted feedback may have assisted in understanding the gaps that prevented successful retrieval of relevant information needed.

ALIGNMENT BETWEEN DIGITAL AND CLASSROOM EXPERIENCES

Students’ perspectives on the alignment, or integration of adaptive courseware with other aspects of courses revealed several common themes. Students noted when they experienced a disjuncture between digital and classroom learning, very often perceived as confusing or frustrating. Alternatively, students also expressed appreciation when digital and classroom learning were aligned, particularly when instructors made transparent the class’s progress, and/or how class sessions would reflect what had happened in the adaptive platform coursework prior to class. A related pattern noted across courses in the PSU study was that students who perceived adaptive and classroom learning as aligned were also more likely to agree or strongly agree with survey items connected to benefits for learning, such as identifying strengths and weaknesses, and feeling more prepared for classes and exams.

The purposeful integration of digital with other course elements has been addressed in literature on blended learning (Garrison & Vaughan, 2008). Blended learning, broadly defined, is a blend, or mix of digital and face-to-face contexts. The incorporation of digital learning via adaptive platforms into traditional classroom-based courses can be seen as one form of blended learning (Kakosimos, 2015). Blended learning scholars and practitioners have observed that integrating various components - achieving the blend - is one of the most difficult challenges for instructors when planning and teaching in blended formats (Caufield, 2011; Linder, 2017). Qualitative student data were replete with observations about integration. The faculty members in the adaptive projects also commented on the complexity of integrating to get the right blend.

Graham and Robison (2007) described a continuum of blended courses according to the type and nature and course organization and activity. *Enabling blends* combine classroom and technology-mediated formats primarily for purposes of convenience and access. *Enhancing blends* are undertaken for purposes of enhanced pedagogy, more active learning, and/or for increased student or instructor productivity. *Transforming blends* align digital and classroom learning such that effective blended practices are highly integrated throughout multiple dimensions of courses, and are deliberately undertaken for pedagogy focused on more engaged learning (p. 90). The researchers wondered whether enabling and enhancing blends could become stepping stones to more transformational course practices, or whether they were “final destinations” for integrating technology into existing course practices.

Deliberate integration in blended formats often requires some departure from previous teaching assumptions and practices for some faculty. Shadiow (2013) observes that making significant changes to teaching practice is often a lengthy, iterative process. Across the campus case study experiences, some course design changes were implemented readily, while others were more challenging and/or took much more time to incorporate. It is reasonable to assume that practices implemented initially in adaptive courses were those perceived as most relevant and valuable, based on instructors' previous experiences and practice. Below we conclude with questions for additional investigation regarding blended adaptive learning models that could further promote student engagement and success.

QUESTIONS FOR FURTHER INVESTIGATION

Future investigation of courses that incorporate adaptive learning could focus on which elements of course design are having the greatest impact on student learning. For example, are there specific aspects of adaptive platforms that are particularly helpful or challenging? Are there specific classroom activities that help students connect their prior knowledge from adaptive work and extend that knowledge in class?

Another direction for further research is to explore what best practices for course redesign might be most useful for faculty as a guide or goal. For example, design models might benefit from more discipline-relevant examples of alignment practices specific to adaptive courseware. Instructors may benefit from direct experience with applied examples of classroom activities that reinforce or extend students' digital learning progress, as well as examples of how learning analytics across a large enrollment course can be quickly assessed and used to modify lesson planning.

Finally, how are faculty making use of assessment in adaptive classroom models, and what are the challenges in responding to analytic platform data? Future research could explore the more useful analytic data points that faculty use to make informed decisions regarding their teaching.

Adaptive courseware holds much potential for a more personalized digital learning experience, and the cases presented here demonstrate that incorporating these learning technologies into courses can also necessitate revisiting some assumptions about course development and design, including assumptions about student engagement. Adaptive blended courses with student engagement at the core multiplies opportunities afforded by emerging technologies within blended course design.

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