SUNY FACT² Adaptive Learning Task Group

Final Report – May 2020

Executive Summary

Adaptive and personalized learning systems provide each student with an educational path that is customized to the needs of the learner. An extensive body of educational research indicates that student learning is enhanced when students engage in frequent practice and receive prompt feedback on their work. Adaptive and personalized learning systems provide both of these without requiring additional effort by the course instructor after the initial investment of time.

There is a growing body of evidence that indicates that adaptive learning systems can increase student learning, provide students with a greater sense of autonomy and improve student confidence, improve student persistence and completion, and reduce the problem of academic dishonesty. One concern about many of the early studies of adaptive learning, though, is that they are based on small sample sizes, suffer from potential sample selection bias, and may also be subject to publication bias.

There are some concerns about the adoption of a single adaptive learning platform for the entire campus. One platform may be most effective in chemistry while another is more useful, for example, for statistics. Some of the most successful campus adoptions, for this reason, have involved the adoption of multiple platforms to allow departments to select the platform that works best in their discipline. Because the market for adaptive and personalized learning platforms is still in a relatively early stage of development, there is some instability as firms enter and leave the market. In some cases adaptive learning platforms have disappeared as content providers after being purchased by major publishers. This instability is especially problematic because the cost of content development in these platforms is generally high. Content created in one platform is not usually easily ported to alternative systems due to the lack of interoperability standards. Adaptive learning systems differ substantially in terms of the ability of faculty members to alter the structure and content of the courses. Concerns are also sometimes expressed about privacy and accessibility issues of commercial platforms.

While there is some question about the quality of some of the existing research, there seems to be sufficient evidence of the efficacy of adaptive and personalized learning systems to encourage an expanded use of adaptive and personalized learning platforms within the SUNY system. Specific recommendations are provided in the Recommendation section of this report.

Background

The SUNY FACT2 Adaptive Learning Task group was created in May 2018 to:

- investigate the effectiveness of adaptive and personalized learning platforms in increasing student learning,
- increase awareness of adaptive learning approaches,
- encourage the consideration of effective implementations of adaptive or personalized learning approaches,
- provide recommendations to relevant parties on policies and procedures regarding the adoption of effective adaptive learning approaches, and
- provide resources to assist campuses in adopting adaptive and personalized learning systems.

During the 2018-2019 and 2019-2020 academic years, the task group:

- conducted a survey on the use of adaptive learning in SUNY
- conducted interviews with faculty, staff, and administrators involved in the adoption, use, or support of adaptive learning platforms at the University of Central Florida, Colorado Technical College, Northern Arizona University, the University of Mary Washington, Erie County Community College and SUNY Albany that had adopted implementations of adaptive learning at their institution.
- met with representatives of the RealizeIt, CogBooks, Waymaker, and SmartSparrow adaptive or personalized learning systems.
- conducted a series of webinars on adaptive learning during the spring 2019 semester.
- worked with the open education task group to provide a Symposium on open pedagogy and adaptive learning during the fall 2019 semester.
- worked with SUNY OER Services, Lumen Learning, and the Association of Public and Land Grant Universities in planning for an Adaptive Learning Day, planned for April 19, 2020. This event was postponed in response to the global COVID-19 pandemic and converted into converted into a series of 4 two-hour sessions of a SUNY Symposium on Adaptive Learning that took place on four consecutive Wednesdays beginning on June 24, 2020. Recordings of these sessions are available as a SUNY CPD playlist.

Members

The task group membership consisted of:

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Introduction

What is Adaptive Learning?

Adaptive learning is a digital instruction method that provides a personalized (Bower, 2016; Bailey, Vaduganathan, Henry, Laverdiere, Pugliese, 2018) and customized learning experience based on learner inputs and interactions within a web-based platform (Liu, McKelroy, Corliss & Carrigan, 2017). The adaptation occurs based on assumptions about the user inferred by their interactions in the platform and stored in the user model (Nakic, Granic, & Glavinic, 2015). These systems use a data-driven and sometimes non-linear approach to teaching and learning (EDUCAUSE Learning Initiative, 2017). Adaptivity is invoked by the machine; adaptability is enacted by the user (Bower, 2016). Adaptive learning technologies include content and assessment, which is scoped and sequenced to support an entire module or course, (Vignare, Lammers Cole, Greenwood, Buchan, Tesene, DeGruyter, Carter, Luke, O'Sullivan, Berg, Johnson & Kruse, 2018). The dichotomies of the adaptive learning tools are that: the technologies can be supplemental or they can be the whole course; they can be open or closed-content models; they can feel personalized, but provide instruction at scale (Brown, 2015; Bower, 2016).

The technology has the ability to monitor student progress, modify instruction, evaluate and assess learning in real time and provide intervention as needed (Brown, 2015; EDUCAUSE, 2018).The adaptation itself can take various forms including: interface based, learning flow based, content based, interactive problem-solving support, adaptive information filtering, adaptive user grouping, adaptive evaluation, and on-the-fly changes (Bower, 2016).
Because of its responsiveness, adaptive learning can accommodate geographically diverse populations (Dziuban, Howlin, Moskal, Johnson, Parker, & Campbell, 2018). The technology accommodates students who wish to accelerate their progress as well as those needing remediation so courses no longer *teach to the middle* (EDUCAUSE, 2018).
The 2018 Horizon Report (EDUCAUSE) lists adaptive technologies, which is closely linked to

data analytics, as an important development in educational technologies for higher education within **a two-to-three-year time-to-adoption timeframe**. An innovative program highlighted in the report at National University in California, was one of the first to begin admitting students on a rolling basis because of the flexibility of adaptive tech.

What is the Waymaker personalized learning system?

The Waymaker system created by Lumen Learning is designed to provide students with many of the same features as adaptive learning systems, but instead of using a computer guided path through the subject matter content, it provides students with recommendations and guidance on the learning path that should be followed to attain content mastery. As in adaptive learning systems, each course module begins with a pre-test to activate and assess prior knowledge and to discover misperceptions. This information is used to provide students with information on where they should focus their learning activities. Students work through a mix of text, videos, and interactive learning objects with regular formative assessments that provide students with feedback on their mastery of the relevant content. Color coding is used on blocks of content to indicate the level of their achievement. Students are encouraged to complete end-of-module tests only after they have mastered each content block. If they score below a mastery threshold on the first attempt, they are given feedback indicating what areas they need to develop and are given a second attempt on this test.

The Waymaker and adaptive learning platforms both:

- provide students with extensive retrieval practice,
- allow students to use their time more efficiently by devoting more time on the areas where they need it the most

What are the educational benefits?

Several studies suggest that adaptive and personalized learning systems can offer benefits in the form of:

- increased student learning in some disciplines,
- a reduction in achievement gaps for minoritized and first gen students,
- increased student perceptions of autonomy,
- improved student confidence,
- increased persistence, engagement, and completion,
- reductions in instructional cost and increased access,
- reduced academic dishonesty

A summary of this research is provided below.

Impact on Student Learning

Research on human learning provides remarkably consistent results on the importance of retrieval practice, the importance of feedback, and of building metacognition in learning. Good discussions of these studies may be found in Agarwal and Bain (2019), Miller (2014), Brown et al. (2014), Eyler (2018), and McGuire (2015). While instructors can provide students with regular feedback on their performance on tests, projects, written assignments, etc. providing students with regular individualized feedback can require a great deal of the instructor's time, especially if the instructor is providing students with learning activities customized to the student's individual needs. This is especially true in the larger introductory classes that are common in many disciplines, especially in the STEM fields.

Adaptive and personalized learning systems, though, provide students with extensive opportunities for retrieval practice, provide students with immediate feedback, and deliver a mix of learning activities and formative assessment that is customized to the individual student's needs, while reducing the demands of instructors to perform repetitive and tedious grading tasks, allowing instructors to focus more time on the development of students' higher-order skills. The automated feedback provided by the system is also expected to improve students' metacognition, reducing the Dunning-Kruger effect (Krueger & Dunning, 1999) and reducing the fluency illusion that students often experience by the common study practice of repeated re-reading of text materials.

A variety of studies (Bryant, 2016; Liu et al, 2017; EDUCAUSE Learning Initiative, 2017; Bailey et al, 2018; Renick, 2018, Fautch, 2019) have found evidence that adaptive and personalized learning systems increase student learning in some content areas.

Bryant (2016) provides a report on the adoption experiences at a variety of institutions. This report notes that the University of Texas at Austin used the Brightspace LeaP platform in its Doctor of Pharmacy program in 2012 with a group of 125 incoming PhD students in a non-credit environment to provide the students with a similar level of entering proficiency in chemistry, biology, information literacy, and math. Statistically significant learning gains were found with the strongest results in chemistry.

Hagerty and Smith (2005) found that the introduction of ALEKS into four sections of a college algebra class at a small midwestern university in 2003 resulted in significant learning gains relative to a control group of four sections that did not use ALEKS. Four instructors each taught one section with ALEKS and one without ALEKS. A random process was used to determine which section would use ALEKS for each instructor. They found that the use of ALEKS resulted in larger learning gains using a pre-/post-test measure in a sample of 251 students.

In a followup study, Liu et al. (2017) analyzed the experiences of 128 students in a PhD program in 2015 in a "large southwestern university." These students were given the option of participating in the same mix of adaptive learning experiences. 74 students participated in the biology module, 52 in the chemistry module, and 62 in the math module. Student performance in these modules was assessed using a pre-/post- evaluation using questions developed by faculty in the program. While there were positive gains in all areas in which students completed at least one learning path, only the chemistry results were statistically significant at a 5% significance level. The results of this study should be treated with some caution because of the small sample size and the self-selection of individuals into the treatment and control groups.

Renick (2018) found that the introduction of adaptive learning at Georgia State reduced the failure rate in introductory math classes by 35%. Renick argues that this introduction, combined with other success initiatives (chat-bots and academic analytics) resulted in 2,800 more students each year.

Dziuban et al. (2016) examine the effect of introducing the Realizeit adaptive learning platform in fully online sections of introductory psychology classes in the fall 2014 and spring 2015 semesters. 72% of the 292 students in these sections reported that they believed that the system provided them with the feedback needed for them to stay on track. They found that on average, students completed 94.7% of the content nodes in the class. The bottom 20 students, however, only completed 54% of the nodes. This suggests that data from the platform provides useful feedback in identifying at-risk students.

Gebhardt (2018) examined the use of McGraw-Hill's LearnSmart adaptive learning platform in 5 sections of an introductory microeconomics class. It was found that students that used more of the assignments had significantly higher grades. This study, though, is subject to a rather severe sample selectivity problem since higher performing students tend to complete more assignments. She recommends that when such a system is introduced that the adaptive learning assignments be graded as a low-stakes assessment to encourage a higher level of use.

A 2018 SRI research report (House et al, 2018) examines the effect of introducing adaptive and personalized learning platforms to 138,000 students and more than 1,000 instructors at 448 higher ed institutions between 2015 and 2017 through a Bill and Melinda Gates Foundation grant. 63% of the faculty agreed that the courseware supported deep learning and increased student engagement (House et al, p, ES-5). 88% of faculty were moderately or highly satisfied with the courseware. The results of this study were mixed. In the 25% most successful implementations, the average student's performance increased from the 50th percentile to the 62nd percentile or higher (House et al, p. ES-6). The average effect of the introduction of this software increased the average student's performance from the 50th to the 54th percentile. We should also note that House et al, (2018) found that, while the overall effect is positive, the introduction of adaptive and personalized learning platforms in some courses had either no significant effect or, in a small number of cases, a statistically significant negative effect. The variability in outcome may be due to differences in course design or the quality of the specific platform in that discipline.

The SRI study found that the effect of introducing adaptive and personalized learning systems varied by institution type, with a significant positive effect in four-year colleges and a statistically insignificant effect in two-year colleges (p. ES-9). The largest positive impacts occurred in biology, psychology, and math/statistics (p. ES-9); insignificant effects were found in business and economics courses. Students in large-section courses gained the most by the introduction of adaptive and personalized learning systems.

Effect on Achievement Gap

A large meta-analysis (Means et al, 2010) found that face-to-face and online instruction result in roughly equivalent learning outcomes, while blended learning approaches outperform both face-to-face and online instruction. Two relatively recent studies (Figlio, 201l; Jaggers, 2011), though, find evidence that online or blended courses in college may widen the achievement gap for minoritized students and students from low-income households. As online and blended learning approaches become more common, this raises concern about the role that higher education may play in increasing income and wealth inequality. House et al. (2018), though, found that low-income students using adaptive or personalized learning software had scores that were a statistically significant 0.1 standard deviations higher than for low-income students in classes in the control group.

Yilmaz (2017, p. 4) notes that “traditional instructional approaches have not been successful in narrowing and closing the achievement gaps in mathematics between black and white students, as well as economically disadvantaged and affluent students.” He found, however, that the introduction of ALEKS adaptive learning significantly reduced the achievement gap in math for minoritized and special education middle school students in a sample of 1110 students in grades fifth through ninth. The effect for students from minoritized racial groups were, however, mixed. Half of the implementations significantly reduced the racial achievement achievement gap, while half showed no significant reduction. In one case, there was a significant increase in the achievement gap (p. ES-7).

Student Perceptions of Autonomy

The use of adaptive and personalized learning systems provide students with the ability to deepen their understanding by spending more time interacting with the platform. There is some evidence that this provides students with a greater sense of autonomy (Fautch,2019).

Student Confidence and Metacognition

Providing students with frequent feedback provides them with an opportunity to improve their metacognition and become more confident in their ability to be successful (EDUCAUSE, 2018). Liu et al. (2017), in a qualitative analysis of the student’s voluntary participation in the use of the LeaP platform for students beginning a doctoral pharmacy program found that a lack of confidence in their content knowledge was a significant factor in their decision to use particular modules. Students report that adaptive courseware provided useful information to them about their strengths and weaknesses (Personalized Learning Consortium and Association of Public Land-Grant Universities, 2017). This feedback allows students to develop the metacognitive skills that are necessary to become a self-directed learner.

Student Persistence, Engagement, and Completion

When all students are expected to learn all content, the instructor often targets instruction content appropriate for the median student. Students that have had more limited preparation often are lost while those with more extensive background in the material become bored and disengaged. Adaptive learning adjusts the level of difficulty in a manner that can keep all students in Vygotsky's zone of proximal development (Vygotsky, 1987), providing all students with a level of challenge appropriate for their existing level of understanding.

- Persistence, engagement, and completion (Murray and Pérez, 2015; Liu et al., 2017; Dziuban et al, 2018; Vignare et al., 2018)
- Reduced the failure rate in introductory math classes by 35% at Georgia State University (Renick, 2018)

Educational Costs

The introduction of adaptive and personalized learning platforms, especially those that rely on open educational resources for content, may significantly reduce educational costs by eliminating the need for expensive publisher-provided textbooks. The SRI study (Means, et al, 2018) found that instructional costs were significantly lower for courses that used personalized and adaptive learning platforms in 8 of the 9 cost analyses conducted in the study. The cost reduction came primarily by eliminating the need for high-priced college textbooks. To the extent to which these platforms increase student success and retention, further cost reductions are also possible.

Murray and Perez (2015) argue that the use of adaptive and personalized learning platforms may provide a solution to the "iron triangle" of quality, cost and access by providing high quality individualized instruction personalized for the needs of each learner at a low cost. Vignare et al, (2018) provides a similar argument.

Academic Dishonesty

Since each student has a personalized learning path, opportunities for academic dishonesty are reduced (EDUCAUSE Learning Initiative, 2017).

What are the Downsides?

There are some potential challenges associated with the adoption of adaptive and personalized learning systems:

- One platform does not meet the needs of all discipline
- Providers may be here today and gone tomorrow
- High cost of developing new course content
- Lack of data interoperability
- Student data privacy concerns
- Adaptive learning platforms may create a sense of isolation
- High start-up costs

Each of these issues is discussed below.

One Platform does not meet the needs of all disciplines

The quality of adaptive or personalized learning solutions varies not only with the platform itself, it also varies with the quality of the content. A platform that works well in one discipline or with one set of students may not work as well in a different discipline or with a different population of students. It is a challenge to find a commercial adaptive learning platform that can meet the needs of all faculty (Personalized Learning Consortium and Association of Public Land-Grant Universities, 2017). Consideration of domain-specific learning theories is essential for development of specific subject area learning systems (Xie, Chu, Hwang, & Wang, 2019).

<u>Providers may be here today and gone tomorrow</u>
Platforms change and at times the landscape can be confusing; some closed content solutions rely on open-content platforms. An example is Knewton which used to be an open-content provider and now deals exclusively with publishers for closed-content applications (Brown, 2015). The Acrobatiq platform was similarly acquired by VitalSource.

<u>High cost of developing new course content</u>
Adaptive and personalized learning platforms differ substantially in terms of faculty created content. At one extreme, some packages consist of entirely plug-and-play course content with little or no customization possible. In these systems, new courses must be developed through a collaborative effort of the platform developer and the faculty user. At the other extreme, some platforms provide an interface that allows users to develop their own course. Appendix A includes information on the extent to which users can create or modify content in the platform.

<u>Lack of data interoperability</u>
The combination of a relatively high cost of developing adaptive learning courseware and instability in the market for providers of these systems would be less of an issue if there was a standard for data interoperability. Institutions are also faced with difficulties integrating adaptive learning solutions into existing learning management systems and faculty and student workflows; there are not only data interoperability issues to overcome, but users are often faced with multiple log-ons. (Bryant, 2016).

At this point, standards have yet to be developed. Groups such as IMS Global, though, are working on developing interoperability standards (EDUCAUSE Learning Initiative, 2017).

<u>Student data privacy concerns</u>
As noted by Meinke (2018), the end-user license agreement for publishers is often vague. This raises issues of how student data might be used by the provider. MacCarthy (2015) reports on a complaint by the Electronic Frontier Foundation that Google allegedly violated their K-12 privacy pledge in which Google gathered information on student browser history and bookmarks. Giving data to 3rd-party vendors reduces the ability of colleges and universities to limit access to this data.

Adaptive learning utilizes student data while in the system not only to personalize the learning Experience, but to improve the system itself. This transaction is not always transparent; ownership of content is claimed by providers via the Terms of Service (Wiley, 2013).

Terms of Use and Privacy Statements from providers the committee researched are located in Appendix B.

Adaptive learning platforms may create a sense of isolation

As noted by Dziuban et al. (2016), adaptive learning platforms, by themselves, do not build a sense of classroom community. 75% of the students enrolled in online General Psychology classes reported that they perceived themselves as interacting less than their peers. As noted by Nunn (2018), a sense of connection, while important for all students, is especially important in helping first-generation and first-year students be successful. While adaptive and personalized learning systems are effective in helping students learn, so are peer interactions. A well designed course will also include activities that build a sense of classroom community. Adaptive learning in conjunction with OER and open pedagogy opens up the possibility of more directed learning (EDUCAUSE Live! Exploring the Horizon Report, 2018).

High start-up cost

Adaptive solutions can be time-consuming and costly to implement (EDUCAUSE Learning Initiative, 2017). Effective implementations result require substantial time investments by faculty and instructional designers. Department-wide adoptions of a given platform for multi-section courses, though, can lower this cost. Multi-year adoptions of a platform can further lower the cost per student of introducing adaptive and personalized learning systems.

Adaptive learning and accessibility

An important aspect to remember when utilizing adaptive learning is that many students still do not have equal levels of access to information technology. This effect of the "Digital Divide" is often forgotten, as students are seen to be "Digital Natives" by many, but this is rarely universally true (Van Dijk, 2006). While students may have access to technology on campuses, the recent COVID-19 pandemic has shown that many have had issues with not only hardware and devices, but adapting to the internet access available in the household.

Adaptive/personalized learning systems have been developed for traditional computers and devices and not mobile or wearable devices leaving some students unable to access them (Sun, Norman & Adbourazakou, 2018; Xie, Chu, Hwang & Wang, 2019).

When applying adaptive learning, it is important to recognize what access students have to all interfaces with the adaptive learning system. Do students need to login to a course shell? Are alerts sent electronically via email, or SMS texts? Do students have accessibility concerns such as color blindness, limited motor skills, or language barriers? These are all questions that should be addressed when selecting an adaptive or personalized learning platform.

ADA Accessibility Statements from providers the committee researched are located in Appendix B.

Adaptive and Personalized Learning Use in SUNY

The task group conducted a survey of adaptive and personalized learning software use in SUNY with repeated requests for survey responses. The surveys asked respondents about the extent to which adaptive and personalized learning systems were used at the institution. A total of only 13 responses were received. These few responses, though, suggested that there were no known large-scale adoptions of adaptive learning platforms other than ALEKS, Waymaker, and publisher-provided platforms.

Lessons from Other Institutional Adoptions

Pedagogy is a driving force in adaptive learning (Murray and Pérez, 2015). The technology is not driving the work, instead collaboration and research are driving the technology. A partnership of the University of Central Florida (a large public university), Colorado Technical University (a successful for-profit university), and tech provider RealizeIt concludes that adaptive technology levels the playing field for students across diverse populations (Dziuban, et al, 2018).

In 2015, research was done by Tyton Partners (Bryant, 2016) using qualitative research methods with leaders in 20 early-adopting institutions and 35 adaptive learning providers. The results were four recommendations of lessons learned. The first is to pilot with implementation in mind and tackle the system integration issues early in the process. Secondly, it is imperative that faculty input drive the process from beginning to end. Institutional decision makers need to ensure all stakeholders expectations are reflected in a coherent process. And, lastly, make sure that product(s) are selected after a full understanding of the landscape is gleaned. Cavanagh, Chen, Lahcen, and Paradiso (2020) recommend best practices for instructors teaching with adaptive courses: 1) understand how the system works, particularly its grading system; 2) understand the system learning analytics in order to know how the student is progressing; 3)target challenging concepts and a flexible teaching mindset; 4) based on the system analytics give students personalized interventions.

In a joint report by the Association of Public and Land-Grant Universities and Every Learner Everywhere (Vignare et al, 2018), a model for adaptive learning implementation is presented. Eight institutions partnered in this report: Arizona State University (ASU), Colorado State University (CSU), Georgia State University (GSU), Northern Arizona University (NAU), Oregon State University (OSU), Portland State University (PSU), University of Louisville (UL), University of Mississippi (UM). An adaptive courseware implementation path is suggested that includes six clear phases:

- PHASE 1 Establish Support (stakeholders and project management)
- PHASE 2 Discover and Decide (align courseware with goals)
- PHASE 3 Design
- PHASE 4 Develop (platform, content, evaluation, user support, integration)
- PHASE 5 Pilot and Iterate
- PHASE 6 Scale

Tesene (2018), O'Sullivan (2018), and APLU (2017) provide additional case studies that offer useful guidance for institutions adopting adaptive learning platforms.

Choice of Platforms

As noted above, there is no platform that works best for all disciplines in all institutional settings. A common approach in successful adoptions has been to provide departments with a set of platform options and to allow the departments to evaluate which platforms offer the most promise for their applications. Some guidance in selecting these platforms is provided by the SRI study (House, 2018) and the work done by the Association of Public and Land-Grant Universities (APLU, 2018).

Recommendations

We recommend that:

- Efforts to increase the adoption of adaptive and personalized learning systems in SUNY receive receive high priority given the current high level of fiscal insecurity and uncertainty about future instructional modalities (including emergency remote learning).
- Priority should be given to the use of platforms that rely on open educational content to reduce educational costs. For this reason, we recommend that SUNY OER Services take a lead role in expanding the use of adaptive and personalized learning systems. Mark McBride, from SUNY OER Services was instrumental in working with the task group and organizing the SUNY Virtual Symposium on Adaptive Learning.
- SUNY facilitate studies of the effectiveness of adaptive and personalized learning systems in a variety of disciplines.
- Information be collected centrally to track uses of adaptive learning to facilitate mutual support and research on the effectiveness of this platform.
- Support be provided to a community of practice (including the use of the SUNY Workspace group).
- A variety of platforms be provided.
- A defined process by provided for faculty to find and implement adaptive solutions and for help and support.
- Marketing/Sharing of whatever OER Services is offering/supporting (including the sharing of the task groups' websites).
- The adoption of pilot programs be funded to provide incentives (such as financial, time release, and consideration for promotion and tenure) to faculty to examine the effects of adaptive learning on accessibility, equity, inclusion, student success indicators, and retention.
- Discussions be encouraged with campus technology and faculty governance during the adoption process.

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APPENDIX A

Adaptive Learning Systems Key Characteristics

Provider	Prepackaged course materials?	User created course materials	Frequency of Adaptivity (how often the system can receive information and change)	Integrates with LMS
Acrobatiq	off-shelf courseware preloaded with modifiable content	authoring platform and ID services	High	LTI, APIs
ALEKS	off-shelf courseware, preloaded content cannot be modified	no	High	LTI, Shibboleth
Brightspace LeaP	no	authoring platform and ID services	High	LTI, QTI, Caliper
Candela - Lumen	courseware preloaded with modifiable content	no		LTI, Common Cartridge
Cerego	no	authoring platform and	High	LTI, Common cartridge

		ID services		
CogBooks	off-shelf courseware preloaded with modifiable content	authoring platform	High	LTI, Common cartridge, QTI, LIS, Caliper, API, OAAI
Drillster	no	authoring platform and ID services	High	SCORM
FishTree	no	authoring platform	High	LTI, Common cartridge, QTI, SCORM XAPI
Flat World	off-shelf courseware preloaded with modifiable content	no	Medium	LTI, SSO, Caliper, XML, JSON, CRM, SIS, Shibboleth, SAML

Fulcrum Labs	off-shelf courseware preloaded with modifiable content	no	High	LTI, SCORM, LDAP, XAPI, SAML
Hawkes	off-shelf courseware, preloaded content cannot be modified	no		
LearnSmart and SmartBook McGraw Hill	off-shelf courseware, preloaded content cannot be modified	no	High	LTI
LoudCloud	no	authoring platform	High	LTI, SCORM, Common Cartridge
Lrnr	no	authoring platform		LTI
OHM - Lumen	courseware preloaded with modifiable content			LTI, Common Cartridge
Open Learning Initiative	off-shelf courseware preloaded with modifiable content	no	High	LTI Tutor Message format

Pearson MyLab and Mastering	publisher-based	no		
MathSpace	interactive digital textbook	no		
RealizeIt	no	authoring platform and ID services	High	SCORM, Common Cartridge, QTI, LTI, oAthu, ePub, API
Sherpath - Elsevier	off-shelf courseware preloaded with modifiable content	no	Medium	LTI, Caliper
SmartSparrow	no	authoring platform and ID services	High	LTI
Snapwiz	no	authoring platform	High	LTI
Waymaker - Lumen	courseware, preloaded content cannot be modified	no		LTI, Common Cartridge

APPENDIX B

Adaptive Learning Systems' Terms of Use, Privacy, and Accessibility Statements

Provider	Terms of Use and Privacy Statements	Accessibility Statement
Acrobatiq	Acrobatiq Terms and Conditions of Use Acrobatiq Privacy	Acrobatiq Accessibility
ALEKS - McGraw Hill	ALEKS Terms and Conditions ALEKS Privacy	ALEKS Accessibility
Brightspace LeaP	Brightspace LeaP Terms Brightspace LeaP Privacy	Brightspace LeaP Accessibility
Candela - Lumen	Candela Terms of Service Candela Privacy	Candela Accessibility
Cerego	Cerego Terms of Services Cerego Privacy	Cerego Accessibility
CogBooks	CogBooks Terms of Use CogBooks Privacy	CogBooks Accessibility
Drillster	Drillster Terms of Service Drillster Privacy Policy	
FishTree	FishTree Terms of Use FishTree Privacy Policy	
Flat World	Flat World Terms of Use Flat World Privacy	Flat World Accessibility

Fulcrum Labs	Fulcrum Labs Terms of Service	Fulcrum Labs Accessibility
	Fulcrum Labs Privacy	
Hawkes Learning	Hawkes Learning Terms of Use Hawkes Learning Privacy	Hawkes Learning Accessibility
LearnSmart and SmartBook McGraw Hill	LearnSmart User Agreement LearnSmart Privacy Policy	LearnSmart McGraw Hill Accessibility
LoudCloud	LoudCloud Terms of Use LoudCloud Privacy	LoudCloud Accessibility
Lrnr	Lrnr End User License Agreement (EULA)	Lrnr Accessibility
OHM - Lumen	OHM Terms of Service OHM Privacy	OHM Accessibility
Open Learning Initiative – Carnegie Mellon	Open Learning Initiative Terms of Service	
Pearson MyLab and Mastering	Pearson MyLab and Mastering Terms of Service Pearson Digital Learning Privacy Policy	Pearson MyLab and Mastering Accessibility
MathSpace	MathSpace Terms and Conditions MathSpace Privacy	
RealizeIt	RealizeIt Privacy	RealizeIt Accessibility
Sherpath - Elsevier	Sherpath Terms and Conditions	Sherpath Accessibility

	Sherpath Privacy	
SmartSparrow	SmartSparrow Terms and Conditions SmartSparrow Privacy	
Snapwiz	Snapwiz Terms Snapwiz Privacy	
Waymaker - Lumen	Waymaker Terms of Service Waymaker Privacy	Waymaker Accessibility

Appendix C: 2019 Adaptive Learning Webinar Recordings

1.Adaptive Learning in HabWorlds and Beyond - Ariel Anbar (Arizona State University). April 9, 2019
2.Implementing Adaptive Learning: Lessones Learned from NAU - Flower Darby (Northern Arizona University), April 16, 2019
3.Effective Use of the Waymaker Economics Platform - Steven Greenlaw (Mary Washington University), April 23, 2019
4.Waymaker+Statistics = Improved Student Performance - David Usinski (SUNY Erie Community College), May 2, 2019