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Adjusting the Future of Adaptive Learning Technologies via a SWOT Analysis

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Abstract: Adaptive learning has become more popular over the last several years, especially with the increasing need to adapt to students with different needs, interests, and learning preferences. The aim of adaptive learning is to provide students with the means to acquire information according to their training needs and cognitive differences, thus facilitating the learning process of each individual. Adaptive learning can be defined as an individualized adaptation of content and pedagogy implementation according to the needs of participants to increase the effectiveness and quality of learning. In this paper, we evaluate the available literature on adaptive learning technology using a SWOT (strengths, weaknesses, opportunities, and threats) approach. While there is promise in adaptive learning, much work still exists in helping to define best practices for utilizing adaptive learning technology to improve student learning and the student experience.

Keywords: *adaptive learning, SWOT, pedagogy, adaptive learning technology*

Background

Adaptive learning with the use of adaptive learning technologies has become more popular over the last several years, especially with the increasing need to adapt to students with different needs, preferences, and learning processes and to assist instructors in providing customized content, integrated assessment, and swift feedback (Elmabaredy et al., 2020). The aim of adaptive learning technologies is to provide students with the means to acquire information according to their training needs and cognitive differences (Morze et al., 2021), thus facilitating the learning process for each individual (Kara & Sevim, 2013).

There are multiple definitions of adaptive learning. The definition used needs to be considered when comparing the literature related to adaptive learning and adaptive learning technologies to ensure the same type of learning is being compared. We suggest using the following definition: adaptive learning is an individualized adaptation of the content and unique pedagogy implementation according to the needs of participants to increase the effectiveness and quality of learning (Alarm et al, 2020; Dzuiban et al., 2017; Kakish & Pollacia, 2018; Morze et al., 2021). This general definition of adaptive learning requires an understanding of several additional terms found in the adaptive learning literature: adaptive learning tools, adaptive content, adaptive sequence, and adaptive assessment. Adaptive learning tools are technologies that synchronize with the learning process and often utilize machine learning. These technologies can adapt to student progress and can change learning in real-time by displaying different content or assessments, or by presenting material in different sequences that match the stage of learning an individual student has achieved, altering the type or timing of feedback, or adapting the pace of learning. Adaptive content means that learning materials are provided in a format that allows students to move at their speed through the material. Adapting content may be achieved by splitting the content into components or by simply allowing the student to choose the volume or format of material that is presented. Adaptive sequencing is the choice of relevant content, difficulty level, and order of study material based on analysis of learning activities such as accuracy of answers on one or more assessments, the number of attempts to complete an assessment, or student interests. Adaptive assessment occurs when the questions that are presented are selected based on the answers to previous questions. For example, more complex questions may be presented after a student answers a simpler question correctly or less difficult questions may be presented after a student answers a more difficult question incorrectly (Morze et al., 2021).

Utilizing adaptive learning technologies can be an effective teaching method, as it allows an instructor to divide materials into smaller parts and to adjust the content to the current level of a student's knowledge (Morze et al., 2021). When reviewing software programs for adaptive learning, it is important to remember that they are classified into three categories: instructor authored, publisher/vendor authored, and Adaptive and Intelligent Web-Based Educational Systems (AIWBES). Instructor authored adaptive learning technology is courseware that allows the instructor to author content, while the software provides the adaptive delivery method. Publisher/vendor authored adaptive learning technology is courseware that is provided by a textbook publisher or other vendor where the content and adaptive delivery method and much of the content are preset, so there is less instructor control of content and delivery (Alarm et al., 2020; Gebhardt, 2018). AIWBES adaptive learning technology builds a model of students' knowledge, preferences, and goals, and then performs some of the roles traditionally performed by a teacher, such as coaching and addressing misperceptions. AIWBES utilizes multiple large data sets containing prior evidence from representative sets of prior learners to develop algorithms which in turn are used to guide how the adaptive learning technology presents material to and interacts with new students. The new information gained from student choices and interaction with the system then becomes the basis for all future adaptive responses (Brusilovsky & Peylo, 2003). Over 30 software companies offer adaptive programs, and each program is unique in its algorithmic approach and ability to customize learning content (Alarm et al., 2020). The selection of software will depend in part on the expertise of the instructor and how much control the instructor wishes to have over the content being provided. In this paper, we discuss the strengths and challenges of using adaptive learning technologies as well as the opportunities for future areas of study for adaptive learning technology to ensure it is being used to its fullest.

Strengths

Perhaps the most obvious strength of adaptive learning technology is evidence of its ability to improve student learning (Daines et al., 2016; Kakish & Pollacia, 2018; Pugliese, 2016). Studies presenting support for adaptive learning technology describe the ability for personalization, increases in student motivation and engagement, insights and benefits that the technology provides instructors and students, and improved student learning outcomes achievement and retention (Cavanah et al., 2020; Denny et al., 2018; Dzuiban et al., 2017; Dzuiban et al., 2018; Elmabaredy et al., 2020; Gebhard, 2018; Hagerty & Smith, 2005; McGraw-Hill Education, 2016; MMHE, 2015; Kakish & Pollacia, 2018; Nakic et al., 2015; Pugliese, 2016).

Personalizing learning

Multiple studies have discussed how adaptive learning can be used as a method to personalize student learning (Alarm et al., 2020; Aleven et al., 2017; Baker & Stewart, 2011, Kakish & Pollacia, 2018; Kara & Sevim, 2013; Pugliese, 2016). Adaptive learning technology helps to facilitate personalized learning by adapting to students' behavior and learning patterns through the use of adaptive assessments (Alarm et al., 2020). The immediate feedback students receive as they move from task to task improves student learning. Because it takes into account students' existing knowledge, skills, and attitudes, the individualized, immediate feedback provided via adaptive learning technology potentially leads to increased and accelerated learning on an individual level (Alarm et al., 2020; Aleven et al., 2017; Baker & Stewart, 2011, Kakish & Pollacia, 2018, Kara & Sevim, 2013; Pugliese, 2016).

Increasing engagement and motivation

Adaptive technology increases student motivation and engagement through the promotion of higher levels of learner confidence (Alarm et al., 2020; Baker & Stewart, 2011; Forsyth et al., 2016; Pugliese, 2016; Sharma et al., 2017). Adaptive learning technology provides multiple methods and tools to increase student engagement, such as artificial intelligence, social networks, blogs, wikis, chats, and discussions (Sharma et al., 2017). While students do need a minimal level of self-motivation to start using and engaging with adaptive learning technologies, studies show that the use of these systems can help students develop this skill further. Adaptive learning technologies lead to increased student motivation by increasing the difficulty of material throughout a course, engaging students actively through providing quick feedback, and identifying success markers for students (Baker & Stewart, 2011; Forsyth et al., 2016; Kabudi, et al., 2021; Pugliese, 2016).

Instructor benefits

Instructors also benefit from adaptive technology, as it provides insights into learners' needs and preferences and allows instructors to track student progress (Alarm et al., 2020; Dziuban et al., 2017; Elmabaredy et al., 2020; Morze et al., 2021; Pugliese, 2016) The systems' ability to track student progress provides efficiencies in time and cost in both teaching and learning (Kakish & Pollacia, 2018; Kara & Sevim, 2013; McGraw-Hill Education, 2016; Moskal et al., 2017; Pugliese, 2016). For these efficiencies to be achieved, however, instructors need to know how to properly use the systems (Cavanah et al., 2020).

Adaptive learning technologies allow instructors to track student progress which also provides insights into the diverse needs of different learners (Alarm et al., 2020; Dzuiban et al., 2017; Dzuiban et al., 2018; Morze et al., 2021; Pugliese, 2016). Progress indicators coded into adaptive systems help visualize student progress. Tracking progress permits instructors to mix competencies that students have mastered with outstanding areas where students have an unmet achievement for a particular topic, thus allowing the instructor to adjust teaching as needed (Dziuban et al., 2017). This ability to adjust topics based on students' learning can help to reduce information overload for instructors and students and can provide support for students as they develop their learning strategies (Elmabaredy et al., 2020). The ability to be able to tailor student learning allows instructors more time in the classroom to apply concepts being learned as opposed to providing knowledge content alone: McGraw-Hill Education (2016) reported that instructors who had implemented their Connect adaptive learning platform spent almost twice as much time in class on concept application and active learning as they had without the Connect adaptive learning platform.

For instructors who wish to conduct adaptive learning, Cavanah et al. (2020) have created an Adaptive Learning Design Framework. This framework has four steps. Step 1 is defining specific learning objectives. Cavanah et al. (2020) suggest writing objectives that students should be able to "master" in an average of 30 minutes. Step 2 is to draft the content, assessment items, and detailed feedback for the assessment items. They note that the best practice is that each lesson should contain five or more assessment questions to ensure students have mastered the content. Step 3 is to create the adaptive learning path. This requires the content to be mapped to a hierarchical structure indicating which topics need to be mastered before moving to more advanced topics. To accomplish step 3, instructors will need to establish the order in which concept mastery is assumed or required by higher-level concepts. Step 4 is to create alternative content and choices for students who wish to have more practice. Proper use of adaptive learning technologies can be a benefit to faculty (Cavanah et al., 2020).

Improved student outcomes and feedback

Adaptive learning technologies have been shown to improve student outcomes and feedback. Improved student learning performance and reduced attrition have been seen in multiple studies (Aleven et al., 2017; Bailey et al., 2018; Bryant, 2016; Elmabaredy et al., 2020; Denny et al., 2018; Dzuiban et al., 2018; Gebhard, 2018; Guerrero-Roldan et al., 2021; Hagerty & Smith, 2005; Kakish & Pollacia, 2018; MMHE, 2015; Muralidharan et al., 2017). Studies have also shown improved students' responses to and perceptions of adaptive learning technology in courses that use such technologies, although student demographics and age, in particular, seem to influence students' responses (Dzuiban et al., 2017; Dzuiban et al., 2018; Guerrero-Roldán et al., 2021; Morze et al., 2021; Nakic et al., 2015).

Student performance and attrition

Student performance in whole courses in a variety of subject matter areas is improved with the use of adaptive learning technologies, especially for students who have lower levels of domain knowledge (Aleven et al., 2017; Bailey et al., 2018; Bryant 2016; Denny et al, 2018; Gurrero-Roladan et al., 2021). One shortcoming of these studies is that they tend to provide general information regarding the outcomes achieved, such as successful course completion, rather than identifying mechanisms and techniques that improve learning outcomes of certain types.

Fortunately, other studies have provided more specifics about areas of learning and resulting assessments that show improvement with the use of adaptive learning technology versus without. Elmabaredy et al. (2020), Gebhard (2018), Kakish and Pollacia (2018), Hagerty and Smith (2005), McGraw-Hill Higher Education (2015), and Muralidharan et al. (2017) provided evidence that test scores and course performance in a variety of subjects improved as a result of using adaptive learning technology. Although many of these studies only indicated "improvement" in exam scores without quantifying the magnitude of that improvement. Kakish and Pollacia (2018) reported that exam scores rose as much as 10% and that course pass rates rose about the same magnitude when adaptive learning technologies were used.

Dzuiban et al. (2018) found that knowledge acquisition, engagement activities, communication, and student growth remained constant in the nursing and math courses across the two universities using the Realizeit adaptive learning software. Kakish and Pollacia (2018) found that the rate of A's and B's earned increased while D's and F's declined in courses using adaptive learning technology. Lastly, Guerrero-Roldán et al. (2021) found that learner attrition was lower in courses using adaptive learning technology versus similar courses without adaptive learning technology.

Student perspectives

Adaptive learning technologies have been found to improve feedback provided by instructors to students (Dzuiban et al., 2018; Guerrero-Roladan et al., 2021). Students report being satisfied with the courses they took that used adaptive learning technologies, and students gave adaptive learning technologies high ratings for educational effectiveness (Dziuban et al., 2017). Adaptive learning technologies, however, are not effective for all students. Students with certain characteristics, such as higher age, are more successful in courses that use adaptive learning technologies, and adaptive learning technologies seem to lead to the most learning success when adjusted based on students' motivation, preferences for particular kinds of learning materials, cognitive style, and background knowledge (Nakic et al., 2015).

Guerrero-Roldán et al. (2021) reviewed the Learning Intelligent System and presented evidence that this adaptive learning system provided students with feedback that students deemed both helpful and appropriate. Dzuiban et al. (2018) conducted a study reviewing the use of Realizeit adaptive learning software in nursing and mathematics courses and also found that student feedback was higher when Realizeit was used. Dzuiban et al. (2018) found that scheduling of material was easier with Realizeit software and that the software gave students more control over the material. The Realizeit software allowed progress assessments to be more authentic and continuous, and students became active participants in their evaluations because they were receiving feedback faster (Dzuiban et al., 2018).

Dziuban et al. (2017) investigated student perceptions of and responses to using the adaptive learning platform Realzeit. Students in the study were from two different universities, the University of Central Florida (UCF) and Colorado Technical University. Students from both universities reported that adaptive learning technology provided by Realizeit was educationally effective, although students at UCF indicated that they did not interact with their peers as much while using the Realizeit adaptive learning platform as they did in courses without Realizeit. Comparing student experiences in an adaptive-learning course to experiences in a similar, non-adaptive course, Dzuiban et al. (2017) reported that a majority of students at both universities were positive about the adaptive learning course, agreed that the adaptive learning technology became personalized to them over time, and reported that they would take another course using adaptive learning (Dzuiban et al., 2017).

Nakic et al. (2015) reviewed student learning characteristics that predicted students' success with adaptive learning. They explored 22 individual user characteristics to determine which characteristics helped predict success in adaptive coursework. Nakic et al. (2015) found that adaptation of learning systems was most successful when the system adapted to one or more of the following: learning styles, background knowledge, cognitive styles, preference for types of learning materials, and student motivation, as compared with adapting to learner characteristics of age, gender, psychomotor skills, personality, anxiety, emotions, affect, and interaction styles. Overall, Nakic et al. (2015) reported that students' responses were positive toward the use of adaptive learning technologies.

Weaknesses and Threats/Challenges

Despite the strengths offered by adaptive learning technologies, such technologies are subject to several weaknesses and threats/challenges. The weaknesses fall into these categories: faculty concerns, student concerns, and institutional considerations. Faculty concerns include faculty resistance to the technology (Mirata et al., 2020), lack of experience with the adaptive software (Mirata et al., 2020), amount of work required to acquire, implement, and use the systems (Kakish & Pollacia, 2018; Elmabaredy et al., 2020), and loss of instructor control of their course material and design (Mirata et al., 2020). Student concerns include poor implementation (Alarm et al., 2020), technology-related problems (Kara & Sevim, 2013), the complexity of use of the technologies (Mirata et al., 2020), loss of socialization with other students (Alarm et al., 2020), complexities related to integrating materials across platforms (Mirata et al., 2020), and lack of consistent evidence that adaptive learning technologies improve learning outcomes (Griff & Matter, 2013; Hinkle & Moskal, 2018; Murray & Perez, 2015; Yarnall et al., 2016). Institutional concerns include the investment of time and money (Mirata et al., 2020; Morze et al., 2021), student privacy, and ethical concerns (Akgun & Greenhow, 2021; Cai, 2018; Coughlin et al., 2021; Hoel & Chen, 2018; Hogle, 2018; How & Hung, 2019; Sijing & Lan, 2018; Zawacki-Richter et al., 2019), learning management integration concerns (Mirata et al., 2020), and lack of leadership support (How & Hung, 2019).

Faculty Concerns

Mirata et al. (2020) conducted a Delphi study at two universities on the challenges of adopting adaptive learning at the respective institutions. Mirata et al. (2020) pointed to faculty resistance and a lack of experience with adaptive software as reasons adaptive learning technologies haven't been adopted more widely. Other researchers (Elmabaredy et al., 2020; Kakish & Pollacia, 2018) cite the amount of work required to adopt adaptive learning as an impediment. Educators need to create granular knowledge maps for the adaptive learning course and outline every skill and every prerequisite a student needs to learn to master the course objectives and outcomes assessments (Kakish & Pollacia, 2018). Elmabaredy et al. (2020) estimated that 200 hours of development time are required for every hour of instructional content design, as each learning activity must be developed and linked to specific learning outcomes. Other faculty concerns include a loss of control over courses and content, a diminishing role in course design, and a general lack of experience with adaptive software (Dzuiban et al., 2018; Mirata et al., 2020).

Student Concerns

Beyond the faculty voice, students have not wholly been sold on adaptive learning systems despite a few studies which have positive student outcomes. Poor implementation, technology-related problems, and complexity of the adaptive learning system may negatively impact students' learning (Alarm et al., 2020 & Kara & Sevim, 2013, Miarata et al., 2020). Students can feel isolated from social contact by the utilization of these systems and may not be motivated to use them (Alarm et al., 2020 & Aleven et al., 2017).

Another issue is the potential for students to cheat or take a path of easier engagement. Aleven et al. (2017) pointed out that some systems may be subject to "gaming the system" behavior by students, where students use step-level feedback and hints to avoid effortful cognition and engagement and instead get the system to deliver answers. Aleven et al. (2017) noted that not all systems are sensitive to or encourage student self-regulation during learning. Some work has been done on ways to build systems that counteract the "gaming the system" issue through using statistical computations to identify areas in the learning system programs which would be prone to "gaming" so they can be redesigned, but there is still work to be done in this area (Aleven et al., 2017).

Another limitation that faculty and thus students experience is that many faculty do not have all of their assignments in one system due to the measurement of different constructs (knowledge, skills, and attitudes; Mirata et al., 2020; Pugliese, 2016). Student assignments may be administered on a publisher website, an institutional Learning Management System (LMS), an additional third-party website, and potentially through other resources online or on paper. This assignment diversity, while having its advantages, drastically reduces the effectiveness of an adaptive learning system due to the reduction in available data. Reasons for instructors to use various resources include issues like limited publisher content, limited publisher question types, limited publisher tool availability like uploading video lectures with embedded questions, additional pay to use features that are free elsewhere like clicker questions, availability of proctoring services like Respondus and Proctorio, and many other niche needs. As a result, an adaptive learning system has only been optimized if all course assignments are feeding data into the system (Johanes & Lanerstrom, 2017; Pugliese, 2016).

Another big student concern is the lack of positive data or very limited positive data that has been found on student outcomes from the utilization of adaptive learning technologies (Griff & Matter, 2013; Hinkle & Moskal, 2018; Murray & Perez, 2015; Yarnall et al., 2016). One reported issue is that students do not attempt case studies presented by the adaptive learning technology, and those that attempt the case studies do not spend quality time on them, thus limiting their learning (Hinkle & Moskal, 2018). Griff and Matter (2013) reported no significant post-test / pre-test improvement in grade distributions or on retention between sections using only adaptive learning technologies versus using online quizzes of equal length in time in an undergraduate anatomy and physiology course at six schools.

Results of the studies by Hinkle and Moskal (2018), and Murray and Perez (2015) are supported by survey results reported by Yarnall et al. (2016). Yarnall et al. (2016) presented results from a study of 19,500 unique students in courses taught by over 280 instructors using adaptive learning courseware. They found mixed results, with most course grades showing no improvement due to the use of adaptive courseware. Yarnall et al. (2016) also reported that successful course completion was not impacted by the use of adaptive courseware. However, they did report a modest, positive effect of adaptive learning courseware utilization on seven sets of learning assessment scores in cases where side-by-side comparisons could be made (Yarnall et al., 2016).

Institutional Considerations

To further complicate the adoption of adaptive learning technologies, institutional challenges need to be addressed. Morze et al. (2021) and Mirata et al. (2020) note that adaptive learning technologies require a substantial investment in both time and money to be effective. LMSs do not integrate well with adaptive systems, and while LMSs can serve adaptive functions, that is not their primary purpose (Morze et al., 2021). Researchers point out that adaptive systems fail to solve the problem of knowledge used in the real world. Cai (2018) pointed out some of the problems that exist for learners when adaptive systems are not wholly adopted into the curriculum. He writes, “Students may still be automatically directed back and forth between learning maps through some courses across the program, but there are some limitations since not all courses in a program include [the adaptive learning system]” (Cai, 2018, p. 108). Even if all courses in a program use the same adaptive learning software, there is little support to ensure that the program is capable of or will track student data throughout their academic program. Furthermore, when student progress is tracked through adaptive learning technology software, students are not asked whether they give the adaptive system permission to apply one or more prior semesters’ data to the new semester (Akgun & Greenhow, 2021). Although many adaptive learning technology systems ask users for permission to use their data (Akgun & Greenhow, 2021), users may remain unaware that the system may be collecting data such as location data, gender or ethnicity data, or the language of the user (Remian, 2019). Privacy of student data is often governed by school districts’ policies (Lynch, 2020), so educators and administrators must consult those policies when considering the use of adaptive learning technologies. State policies vary widely in whether they consider consumers to have control over their educational data (Sridhar, 2021). While parental consent is usually mandated by school district policies, it is not clear how often student permission is sought, nor is it clear the degree to which students under the age of 13 understand how their data is being utilized and shared (Lynch, 2020). A possible detrimental effect of legislation and mandated privacy policies would be excessively limiting educators’ and students’ use of the latest educational technology and adaptive learning platforms that customize student learning to the potential benefit of student success (Sridhar, 2021). If consent is required to participate in an educational experience, given the large number of technologies most students use, it is possible that consent fatigue may lead individuals to grant permission to adaptive learning technologies’ use of personal data without reading details provided by vendors about how the data will be used or shared (Remian, 2019). Moreover, complex legal jargon used when consent is requested may mean users do not fully understand or even read the consent language (Remian, 2019). Clearly, more work needs to be done to protect student privacy and to inform consumers and educators.

Even once the software is adopted, there may be limitations around the judgments the software is making to group students and deliver content. Aleven et al. (2017) noted limitations to adaptive learning technologies that attempt to adapt to students' affect; the authors noted that detecting student body language and expressions may require special software which is not commonly available to most students or institutions. A common barrier to adoption for many institutions is a lack of leadership support for these types of innovative adaptive learning technologies (Mirata et al., 2020). Adaptive learning often lacks a place in the overall university strategic plan (Bailey et al., 2018). Often, it is difficult for institutions and those charged with evaluating adaptive learning technologies to do so independent of vendor explanations of black-box models (How & Hung 2019).

Ethical concerns present possibly the most significant barrier to the widespread implementation of adaptive learning technology. Several researchers point out ethical issues associated with adaptive learning systems. Zawacki-Richter et al. (2019) noted several ethical issues associated with the use of AI-enabled adaptive learning platforms. Systems that monitor student attention, affect, and motivation via facial recognition, physiological monitoring, or eye-movement technology raise ethical and privacy questions as well as questions about the extent to which instructors can make good pedagogical use of such information (Zawacki-Richter et al., 2019). Perhaps the most significant ethical consideration to using adaptive learning technology is the inherent bias that is assuredly present in algorithms powering such systems and the data sets used to train the systems (Hogle, 2018; Sijing & Lan, 2018, Wood, 2021). Sijing and Lan (2018) identified three aspects of ethical concern in the development and use of AI systems in education: algorithm design, incomplete or biased use of data in the development/use of AI systems, and inaccuracy of the input to AI systems. Inaccurate or biased algorithms can cause harm in AI education (Wood, 2021). Data sets used to tune algorithms in AI systems can be limited, inaccurate, and may often be biased (How & Hung, 2019; Knox & Pardos, 2022, Wood, 2021). Systems use both training data and test data or relevance data, and incomplete, inaccurate, or biased data will lead to systems that produce errors and bias (Hogle, 2018). How and Hung (2019) noted that issues may arise also because the role of teachers shifts with the use of AI in education to more of a coaching role. As many adaptive learning systems are black-box systems to the administrators, instructors, support staff, and students who use them (How & Hung, 2019), assessing bias in these systems is difficult and likely impossible for most adopters of adaptive learning systems. Solutions proposed include ethical education for programmers and students studying computer science, as well as diversifying the group of developers designing the algorithms (Wood, 2021). How and Hung (2019) also suggested that teachers have a role in the ethical education of their students by assessing the accuracy of the content conveyed in AI systems. Akgun and Greenhow (2021) remarked that, despite the marketing of AI tools in education as objective tools, the developer/designer embeds inherent bias into the systems. Akgun and Greenhow (2021) also raised privacy concerns, noting that even though users may grant consent to developers to use private information, the users often do not realize the extent of private information encoded in these systems, such as language, location, ethnicity, and behavior patterns. Akgun and Greenhow (2021) discussed ethical issues in AI surveillance systems and in systems that access social network systems to glean data on student behavior patterns. Interestingly, Akgun and Greenhow (2021) raised the issue of autonomy - if algorithms are predicting students' actions, the systems containing those algorithms are inherently biased and limit autonomy (see also Hogle, 2018). Akgun and Greenhow (2021) noted the significant problem of AI algorithms perpetrating historical power structures and biases. Akgun and Greenhow (2021) also discussed educational programs for K-12 students and educators that emphasize and develop an awareness of ethical issues in AI in education which have been developed by the MIT Media Lab and Code.org. Akgun and Greenhow (2021) noted the need for culturally-relevant pedagogies and user-centered education, along with wide access to education on ethical issues in AI-enabled adaptive learning systems.

Privacy issues are a significant ethical consideration when implementing adaptive learning technologies (Quinton & National Journal, 2015; Wood, 2021). Most users are unaware of the diversity and extent of user information potentially captured by adaptive learning technologies (Quinton & National Journal, 2015). Coughlin et al. (2021) noted concerns of fairness, transparency, privacy, liberty, autonomy, and trust, particularly for online web monitoring systems. To these, we might add data security and ethical integration of academic student information systems' data with student learning data captured by adaptive learning technologies (Akgun & Greenhow, 2021). Hoel & Chen (2018) argued for openness, transparency, and explicit negotiation of data sharing with all students. The weaknesses and challenges raised here need to be addressed before the widespread adoption of adaptive learning technologies to protect students from loss of privacy and the impact of bias in coding and algorithms underlying adaptive learning technologies.

Opportunities

The need for further research investigating the potential positive impact on student learning of implementing adaptive learning technologies is supported by Yarnall et al.'s (2016) report on the Adaptive Learning Market Acceleration Program data. While Yarnall et al. (2016) reported mixed results including a lack of substantial support for a positive impact on student learning outcomes from the use of adaptive learning technologies, more recently Every Learner Everywhere has presented several case studies from institutions such as Colorado State University, Oregon State University, and Portland State University showing that an integrated implementation of adaptive learning technologies, research-based teaching, and course redesign in general education and gateway courses improved student success (Every Learner Everywhere, 2020a, 2020b, 2020c). These recent case studies reveal an opportunity to further explore the impact of the integration of faculty development, student-oriented course redesign, and implementation of adaptive learning technologies on student success across institutions.

Conclusion

In this paper, we discussed the strengths and challenges of using adaptive learning technologies as well as the opportunities for future areas of study to ensure it is being used to their fullest. Strengths of adaptive learning include its ability to improve student learning (Daines et al., 2016; Kakish & Pollacia, 2018; Pugliese, 2016) through personalization, increases in student motivation and engagement, insights and benefits provided to instructors and students, and improved student learning outcomes achievement and retention (Cavanah et al., 2020; Denny et al., 2018; Dzuiban et al., 2017; Dzuiban et al., 2018; Elmabaredy et al., 2020; Gebhard, 2018; Hagerty & Smith, 2005; McGraw-Hill Education, 2016; MMHE, 2015; Kakish & Pollacia, 2018; Nakic et al., 2015; Pugliese, 2016).

To realize these strengths, however, the weaknesses and challenges/threats identified in the areas of faculty, students, and the institution need to be neutralized. Faculty resistance to the technology (Mirata et al., 2020) and the lack of experience with the adaptive software (Mirata et al., 2020) could be potentially mitigated through professional development and training guides. The concerns around the work required to acquire, implement, and use the systems (Kakish & Pollacia, 2018; Elmabaredy et al., 2020) would need to be addressed again through training and potentially the addition of a staff member to aid in the use of the system. The faculty concern of loss of instructor control of their course material and design (Mirata et al., 2020) could potentially be mitigated through discussions with the faculty about why and how the systems will be used or potentially ensure systems that are purchased have more instructor control.

Student concerns also need to be addressed. Concerns related to poor implementation (alarm et al., 2020), technology-related problems (Kara & Sevim, 2013), the complexity of use of the technologies (Mirata et al., 2020), and complexities related to integrating materials across platforms (Mirata et al., 2020) can potentially be mitigated through student training and ensuring staff are available to help students when questions arise. The concern around loss of socialization with other students (Alamri et al., 2020) needs to be addressed through the use of other activities in the classroom or online that require students to work with other students as opposed to just the software. The last concern around the lack of consistent evidence that adaptive learning technologies improve learning outcomes (Griff & Matter, 2013; Hinkle & Moskal, 2018; Murray & Perez, 2015; Yarnall et al., 2016) needs to be addressed in the future areas of research discussed in the opportunities section of this paper. This is an area where more research is needed.

Institutional concerns include the investment of time and money (Mirata et al., 2020; Morze et al., 2021), student privacy, and ethical concerns (Akgun & Greenhow, 2021; Cai, 2018; Coughlin et al., 2021; Hoel & Chen, 2018; Hogle, 2018; How & Hung, 2019; Sijing & Lan, 2018; Zawacki-Richter et al., 2019), learning management integration concerns (Mirata et al., 2020), and lack of leadership support (How & Hung, 2019). These concerns are harder to address, and these are areas where more research and work are needed.

As discussed in the opportunities section of this paper, the call for future research seems clear. Further guidance on ethical dilemmas is sorely needed to help ease the concerns of many about the use of adaptive learning systems (Hogle, 2018; Wood, 2021). Additionally, case studies on implementation and adoption at a larger scale would help prove support for the use of adaptive learning systems (see Every Learner Everywhere, 2020a, 2020b, 2020c). Lastly, and importantly, the literature is short on considering student input on the use of adaptive learning systems. What do students think about adaptive learning technology and its impact on their learning? Are they aware of and concerned with privacy issues and the possible reduction in social interaction that such systems may lead to? Dziuban et al.'s (2017) work begins to include students in the conversation, but a deeper and wider content-specific discussion, as well as consideration of student body size and institution type, is necessary to adequately capture the students' voices. While adaptive learning seems to have a potentially promising place in higher education, much work remains to establish the best practices for its use.

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