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Guidelines for Effective Adaptive Learning: A Meta-Analysis

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Guidelines for Effective Adaptive Learning: A Meta-Analysis

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Abstract

Adaptive learning adjusts to the student's needs to improve learning outcomes, but adaptive learning platforms approach this goal in vastly different ways. When tested, these platforms also show varying levels of success in improving learning. The goal of this meta-analysis is to develop guidelines for the creation and implementation of adaptive learning based on studies where adaptive learning was utilized.

Keywords: Adaptive Learning, Instructional Design, eLearning, Adaptive Hypermedia, Intelligent Tutoring Systems

Guidelines for Effective Adaptive Learning: A Meta-Analysis

Introduction

Adaptive learning is a type of eLearning that adjusts to the student's performance. This can include skipping content the student already knows, repeating or reviewing content the student is struggling with, presenting the content in different ways depending on how the student learns best, and offering additional topics based on the student's interests (Bennett, 2018; Dreambox Learning, n.d.). The first efforts at designing adaptive learning experiences were developed in 1995 (Lin et al., 2003) and modern systems can be extremely complex (Chen & Chang, 2015; van Klaveren et al., 2017). Initially, research in this area was focused on the development of the software packages and the underlying algorithms which are used to modify a learner's experience. Significant attention was also given to the theoretical frameworks upon which adaptive learning platforms are built (Phelps, 2019). Until recently, much less attention was given to verifying that these systems are actually as effective as the theory suggests or how to implement them (Alshammari & Qtaish, 2019; Chen & Chang, 2015; Phelps, 2019). This is an important area of research because adaptive courses are significantly more costly and time consuming to develop than one-size-fits-all training.

Adaptive learning platforms can be an effective tool to improve learning outcomes, but not all of the systems examined in this review were successful. This meta-analysis of the literature seeks to identify common traits of adaptive learning platforms and situations where they were effective in improving learning outcomes, as well as traits and situations where adaptive learning made no significant difference or was even detrimental compared to traditional methods. Based on these common traits, recommendations will be developed for the creators of adaptive learning platforms, instructional designers building course materials in these platforms, and the instructors and students selecting and using these materials.

The diversity in adaptive learning platforms and how they are utilized is both a boon and a challenge in this review. While the differences in design and implementation generate a rich pool of data to analyze, it can become a case of comparing apples to oranges when attempting to determine why adaptive learning is effective in some cases but not in others. Another challenge is the differing amount of information about the study parameters provided in each paper. Some authors discuss in great detail the algorithms of the adaptive learning platform and the context where the students use the software, while others omit some or all of this information. Some studies were omitted from this review due to a lack of situational information required to effectively analyze why the system was effective or ineffective. In addition, an emphasis has been placed on examining adaptive learning systems that were not successful or showed mixed results as these provide the greatest opportunities for comparison and analysis. As Bill Gates said, “It's fine to celebrate success but it is more important to heed the lessons of failure” (as cited by Tracy, 2021).

Background

As shall be explored later in this paper, the published research shows that adaptive learning platforms are extremely diverse in their purpose and functionality. They can be designed as a stand-alone system or as a supplement to other materials, including instructor-led courses. While each platform builds a profile of the learners in order to tailor the learning experience, there are several methods of building these profiles, and they do not all consider the same information. The aspects of the learning experience which are adapted for the student can be extremely different from one platform to the next. Finally, the way that adaptive learning platforms are utilized by instructors and students can also vary widely.

Before exploring the differences between adaptive learning platforms exhibited in the published research, it is important to discuss what these various systems have in common.

Definitions

Adaptive learning has been defined in many ways (Bennett, 2018; Dreambox Learning, n.d.; Newman et al., 2015). For clarification, the definitions used within this paper for several key terms are provided here.

Adaptive learning is any method of instruction which is tailored to the individual student. There are many ways of adapting the content to the student including working with human tutors, mastery learning which requires a specified level of competence before proceeding to the next topic, and AIs designed to develop personalized learning plans for students. Computer-based adaptive learning may also be called *adaptive tutoring systems* or *intelligent tutoring systems* (Kulik & Fletcher, 2016; Shute & Psotka, 1994). Many authors limit adaptive learning to computer-based systems (ex. Dreambox Learning, n.d.; Li et al., 2018; Wang et al., 2020), but this review will also consider other methods of adapting educational content to the learner.

Adaptive hypermedia is any form of computer program or interface which builds a profile of the individual user and uses that information to adapt to that individual's needs (Brusilovsky, 2001). Adaptive learning is a subset of adaptive hypermedia. Other examples include online stores which make product recommendations based on your purchase history or websites which save your settings and preferences.

Adaptive courses are any courses which are designed such that at least one aspect of the instruction is tailored to individual students.

Adaptive learning platforms are the software packages used to build adaptive courses. An adaptive learning platform may be designed for a specific adaptive course, or it may be the shell within which many adaptive courses are built and accessed.

A *learning path* is the sequence of instructional materials and activities presented to the student. Learning paths can be tailored to the individual by adding or removing content, presenting topics in a different order, selecting between multiple methods of presenting the same topic, or providing specific feedback and review materials based on the student's performance.

Theoretical Framework

Adaptive learning is primarily based on the *constructivist learning theory* (Phelps, 2019). The fundamental concept of constructivism is that each person builds their own understanding based on their prior knowledge and experiences. Each student's learning experience is, therefore, unique (Western Governors University, 2020). In addition, constructivism emphasizes the use of problem solving and practical experience, both as a way to build knowledge and to demonstrate that knowledge in meaningful ways (Phelps, 2019). Adaptive learning courses frequently use simulations and solving multi-step problems to present content and assess student mastery (Newman et al., 2015).

The *zone of proximal development (ZPD)* was first proposed by the Soviet psychologist Lev Vygotsky (Vygotsky, 1978). Vygotsky asserted that people are able to master more challenging tasks with the support from a *more knowledgeable other* than they can on their own. In this theory, content is divided into three categories: things which are within the student's current skill set or which they can figure out on their own, things which the student can master with assistance, and things which the learner cannot do at their current skill level. The content which can be mastered with assistance is considered to be within the ZPD, and cognitive development occurs when the student receives tasks and guidance appropriate to their current skill level (Vygotsky, 1978). While concept of the more knowledgeable other was originally defined as another person, it has since been expanded to include the support provided through computer-based learning (Newman et al., 2015; Phelps, 2019; van Klaveren et al., 2017). Providing content at the appropriate level also aids motivation by preventing either frustration or boredom (Phelps, 2019; van Klaveren et al., 2017; Yang & Dorneich, 2018)

Another important concept in the development of adaptive learning is *scaffolding*. This is the process of “controlling those elements of the task that are initially beyond the learner's capacity, thus permitting him to concentrate upon and complete only those elements that are within his range of competence” (Wood et al., 1976, p. 90). As the learner gains mastery of the topic, they are given greater control over the performance of the task. In adaptive learning, scaffolding is provided by breaking tasks into steps, providing hints when a student is having difficulty, and providing frequent feedback. A review of 45 publications conducted by VanLehn (2011) showed that computer-based instruction could be as effective or nearly as effective as human tutors. The granularity of the feedback was determined to be the greatest indicator of effectiveness, with more frequent feedback yielding greater effect sizes. However, the data also demonstrated a plateau effect where providing feedback more frequently than at the completion of each problem had diminishing returns for student learning (vanLehn, 2011).

Mastery learning is also an important foundation for many adaptive learning courses. In mastery learning, a student must demonstrate a pre-established level of skill in a topic before progressing to the next topic (Kulik et al., 1990). Students are either self-paced, or they are taught as a group by an instructor with review materials and/or tutoring provided based on test results. In a review of 108 studies, Kulik et. al (1990) found that the improvement in student performance from mastery learning programs was large and statistically significant when compared to instruction without mastery requirements.

The Three Pieces of an Adaptive Learning Platform

Adaptive learning platforms share an overall architecture. Each software package contains three components: a domain model, a learner model, and a pedagogical model or adaption model (Alshammari et al., 2015a; Hafidi & Bensebaa, 2014).

The *domain model* includes the instructional materials and activities which will be used to teach the topics covered by the adaptive course. It also includes the relationships between the materials such as which pieces must come before other pieces, which materials are equivalent methods of teaching the same topic, and a method of determining when sufficient mastery of a topic has been reached (Alshammari et al., 2015a; Hafidi & Bensebaa, 2014). There are multiple methods of constructing the domain model such as network and hierarchy models (Alshammari et. al, 2015a).

The *learner model* includes learner characteristics such as the user's demographic information, their knowledge level, their learning style, and data on how the learner has used the adaptive learning platform (Hafidi & Bensebaa, 2014). The precise characteristics which are collected in the learner model can vary widely because they are closely tied to the pedagogical model or adaption model. The learner model can be static or dynamic (Alshammari et al., 2015a). A static model is built during account creation and does not change. A dynamic model also includes data collected as the learner uses the adaptive learning platform. Dynamic models can use explicit feedback such as correct or incorrect answers to practice problems or bookmarking, and they can also use implicit feedback such as time spent per page and number of page visits (Alshammari et al., 2015a).

The *pedagogical model* (Hafidi & Bensebaa, 2014) or *adaption model* (Alshammari et al., 2015a) builds a learning path for the student based on their learner model. This model determines what aspects of the learning path can be adapted and how the information in the learner model will be used to create a customized learning path. Short memory cycle adaption uses recent user interactions to adapt the course content, such as providing appropriate feedback after an activity. Long memory cycle adaption combines recent user interactions with previous user interactions to create and update the learning path (Alshammari et al., 2015a).

Case Studies

This section examines a variety of studies where adaptive learning was used with varying results. Details have been included about the execution and context of each study. This information is critical for extrapolating why adaptive learning was more successful in some situations than in others. Studies with similar traits have been grouped together for ease of comparison, although some studies could be discussed in multiple categories.

Practice Problems and Revision

There are many types of adaptive learning platforms and many ways to utilize these tools as either stand-alone instruction or as one element of a course. The following examples utilized adaptive learning to provide additional practice problems and/or review materials for students in an instructor-led course.

Van Klaveren et al. (2017) conducted a study involving over 1,000 students in 7th, 8th, and 9th grades over a full school year. Students were encouraged by their teachers to complete practice problems using an eLearning system. Students in the control group received practice problems distributed evenly across all topics and difficulty levels, while those in the adaptive group received questions in topics where their performance was lower than that of the class, and the difficulty of the questions was adjusted to their proficiency level. On average, the group receiving content of adaptive difficulty were presented with more difficult practice questions, and spent longer per practice session, but there was no statistically significant difference in the test scores between the two groups.

In contrast, Ghergulescu et al. (2016) conducted a study involving over 10,000 K-12 students over the course of six months. This study utilized the adaptive learning system Adaptemy. This system recommends topics to students by showing the grade they have achieved for completed topics and offering the opportunity to review these, suggesting topics for the student to learn next, and offering topics which the student might not be ready for but may choose to try. Students who revised a lesson at least once demonstrated a statistically significant increase in mastery and a reduction in the time they took to answer questions in that topic.

Both of these studies involved K-12 students in instructor-led classes who used adaptive learning systems for supplemental practice. In addition, both of these systems identified topics where each student was weak and would benefit from additional practice. Due to the nature of these studies, which involved multiple teachers, subjects, and grade levels, there was variation within each study group for how the adaptive learning platform was integrated into the curriculum. These similarities make a comparison of these studies valuable.

The primary difference between the successful implementation of the Adaptemy system and the unsuccessful implementation of the system to provide practice problems of adaptive difficulty is the type of content available within the program. The successful system included both revision materials to explain the topic and practice problems, while the unsuccessful system only had practice problems (Ghergulescu et al., 2016; van Klaveren et al., 2017). This indicates that using adaptive learning to provide additional practice problems is insufficient to improve learning outcomes. Adaptive learning systems must also include instructional content to be effective.

Supplements to Instructor-Lead Courses

Like the previous examples, this study examines the use of adaptive learning to supplement instructor-led courses in a K-12 environment. Homer & Plass (2015) conducted a 16-week study using the adaptive learning platform Cerego to provide supplemental instruction and practice problems in three subjects for high school students. It was up to the teachers in the seven participating schools to integrate the program into their existing curricula. Some teachers used the software in their classrooms while others assigned it as homework, either to reinforce the topics already covered or to introduce the material which would be taught in greater depth the following day.

Despite the recommendation that students use Cerego for at least 1 hour per week, only 27.3% of students involved in the study used the adaptive learning platform for at least 13 hours over the 16-week study. Many factors contributed to this low participation rate. The availability of computers in classrooms was limited, and some students encountered technical difficulties with the software. The number of other eLearning tools which were already in use for these classes and the amount of work which was being assigned to students also affected the amount of time spent using the software. Finally, the alignment of Cerego lessons with the teachers' lesson plans and the level of buy-in from the participating teachers had an impact on the participation rate as well.

Across all three subjects, a significant positive correlation was found between the amount of time students spent using Cerego and their scores on final assessments. Students who used the system for the recommended 1 hour per week scored significantly higher on average than the control group. However, using Cerego was not uniformly successful for improving learning outcomes. Students who used the system for less than the recommended time scored significantly lower on the final assessment than the control group (Homer & Plass, 2015).

These results indicate that adaptive learning is not a panacea for improving the learning outcomes for students and can even be detrimental if not implemented with care. Adding additional eLearning tools on top of an existing curriculum can actually impede learning. This is particularly true when several other eLearning tools are already in use and time is spent troubleshooting the system rather than exploring content. This may be related to the increase in extraneous cognitive load (Kalyuga, 2010; Sweller et al., 1998) from learning how to use additional software tools.

In addition, if the adaptive learning platform's content does not align with the existing course content, this violates the *coherence principle*, which states that "you should avoid adding any material that does not support the instructional goal" (Clark & Mayer, 2016, p. 151). As with any aspect of instructional design, fancy tools and techniques do not compensate for a poorly considered instructional strategy.

Aligning Adaptive Course Content with Student Skill Level

The following examples both compare the effectiveness of adaptive learning platforms for low-skilled students to the effectiveness for their more highly skilled peers. As previously discussed, content which the student is able to master with assistance falls within the zone of proximal development (ZPD) (Vygotsky, 1978). The greatest gains are thought to occur when the students study content within their own ZPD.

Serrano et al. (2018) conducted two related studies using the adaptive learning platform TuinLECweb. This software was designed to teach strategies to improve reading comprehension, particularly for task-oriented reading where the purpose of reading is to perform a specific task. This adaptive learning platform provides students with adaptive feedback based on their performance and the strategic search decisions they make when answering questions.

The first study conducted by Serrano et al. (2018) included 47 students in sixth and seventh grades. It compared the effectiveness of TuinLECWeb for students with low reading comprehension skills to those with high reading comprehension skills. The second study involved 68 sixth grade students who all scored in the bottom 40th percentile for reading comprehension. This second study compared the effectiveness of TuinLECweb to a conventional curriculum of workbook exercises. Students in the conventional curriculum completed the workbook exercises independently. Teachers were available to answer questions, and these teachers read the correct answers for the workbook activities aloud at the end of each session. In both studies the students took a pre-test, worked with the instructional materials twice per week for four weeks, took a post-test immediately after the end of instruction, and took a follow-up test two weeks after the end of instruction.

The first study found that the curriculum had little impact for students with high reading comprehension. Students with low reading comprehension did not show a statistically significant improvement on the post-test at the end of instruction, but the improvement two weeks later on the follow-up test was significant. The second study verified the results for students with low reading comprehension observed in the first study. It also showed that TuinLECweb was more effective than the conventional method of teaching strategies to improve learning comprehension (Serrano et al., 2018). These results demonstrate that computer-based instruction can be an effective way to teach abstract concepts such as self-regulation strategies. However, such topics may require additional time and practice outside of the period of instruction for the effects to become apparent. They also show that intelligent tutoring systems can be as or more effective than conventional methods of instruction.

In a study by van Seters et al. (2009) students completed a module on enzyme kinetics built within the adaptive learning platform Proteus. This module was utilized as part of an instructor-led course at two universities. The study included two groups of students. Group A was comprised of 37 students at the end of their second year of college. Group A used the module after four 45-minute lectures on enzyme kinetics. Group B included 237 students at the beginning of their first year of college. The final exam for the course included one question about the topics covered in the module.

Students completed the module independently in a classroom setting with an instructor available to answer questions (van Seters et al., 2009). After reviewing the lesson content in Proteus, students could choose easier or more difficult assignments. The assignments were each assigned a number of marks, and each topic within the module required the student to earn a certain number of marks in order to proceed. Both groups were permitted to complete the module at home after the classroom time was completed.

The second year students had a higher completion rate for the module than the first year students. Those who completed some or all of the module scored better on related exam questions than students who did not use the module (van Seters et al., 2009). The second year students rated their own prior knowledge of the topic higher than the first year students did and also indicated that they learned more from the module than the first year students. First-year students considered the module to be more difficult than second-year students did, and only 17 of 237 first-year students completed the module. There was also no difference in test scores between first-year students who finished the module and those who did not. This indicates that the module was too advanced for the first-year students.

The first study by Serrano et al. (2018) and the study by van Seters et al. (2009) both compare the effectiveness of their adaptive learning platforms for more skilled and less skilled learners. In the first example, the students with high reading comprehension skills showed no improvement after completing a course on strategies for task-oriented reading while their low-skilled peers showed significant improvement (Serrano et al., 2018). In the second example, first-year college students found a module on enzyme kinetics too difficult to complete. Second-year students with a higher initial knowledge of the topic completed the module at a higher rate and scored significantly better on a related exam question than those who did not use the module (Seters et al., 2009). Together, these studies highlight the importance of ensuring that the content of an adaptive learning course is within the zone of proximal development for the students.

Self-Paced Adaptive Instruction

The previous examples have either been integrated into instructor-led courses or of a sufficiently short duration that student motivation was not a significant concern. The following studies examine how the way students use an adaptive learning course can impact their learning outcomes.

The LeaP adaptive learning platform was offered to new Pharm.D. students for six weeks during the summer before their first semester (Liu et al., 2017). Use of the adaptive learning platform was completely voluntary, including the amount of time spent and which topics each student reviewed. All of the 128 students who chose to participate received pre- and post-tests generated by experienced faculty. Within the LeaP platform, students received a diagnostic test. The results of this test were used to generate an individualized study plan and practice questions.

The LeaP platform also included a post-test which students could take multiple times to improve their scores.

Analysis of data logged by the system showed that students who used the system more had higher scores on the post-test and practice questions within LeaP. However, neither the usage data from the adaptive learning system nor the learner characteristics such as previous GPA or the level of prior education were a significant predictor of scores on the post-test created by the faculty. The weak relationship between the scores on the two types of post-tests calls into question the alignment between the learning objectives defined by the faculty and the LeaP system's course materials and lesson path recommendations.

A comparison of the four highest and four lowest performing students yielded additional information which can be leveraged to make future adaptive learning platforms more effective. The students with the highest post-test scores within LeaP viewed more learning paths, accessed more pages of content, and viewed more supplemental materials than their lower-scoring peers, but spent less time on each page (Liu et al., 2017). The overall time spent in the system by high and low performers was not reported so no conclusions can be drawn about how the longer amount of time spent per page by the low-performing students impacted the number of content pages they viewed. However, it is clear from both this study and from the study of the Cerego system discussed previously (Homer & Plass, 2015) that encouraging learners to spend more time in the adaptive learning system and to view more of the instructional materials available is a key element of maximizing the effectiveness of these eLearning tools.

Chen and Chang (2015) conducted a study involving 130 students in ninth grade. In the adaptive group, the pre-test adjusted the difficulty of the questions based on previous responses, and these students were assigned to up to three units of content. The control group was given a static pre-test and they had access to all of the available materials in a learner-controlled environment. All students studied until they felt they were ready for the post-test.

The difference in post-test scores between the two groups was not statistically significant. However, the adaptive group spent significantly less time on both the pre-test and studying the materials (Chen & Chang, 2015). This experiment gives compelling evidence to the theory that adaptive learning systems make learning more efficient.

Student Perceptions of Adaptive Learning

Student motivation is a significant concern in adaptive learning. As previous studies have shown, the amount of time spent using an adaptive learning platform has a positive effect on learning outcomes (Ghergulescu et al., 2016; Homer & Plass, 2015; van Seters et al., 2009). The studies in this section examine how adaptive learning platforms are perceived by the students who use them.

Alshammari et al. (2015a, 201b) conducted two related studies using the adaptive learning platform AdaptLearn. The AdaptLearn platform first assessed each student's learning style using the information perception dimension of the Felder-Silverman model (Felder & Silverman, 1988). In this model of learning style, it is proposed that "sensing learners may benefit more from concrete information such as facts and examples; intuitive learners may perform better with abstract concepts such as theories and mathematical models" (Alshammari et al., 2015a, p. 13). The sections of content in the adaptive learning course were divided into two categories: concepts and math notation were classified as abstract while examples and practice tools were classified as concrete. All students received every section of content, but the order of presentation was adjusted based on learning style.

In the first study by Alshammari et al. (2015a), 60 undergraduate students used AdaptLearn to study topics in cryptography which were outside of their normal curriculum. Students in one group received the sections of content which aligned with their learning style first, while students in the other group received the content which aligned with their learning style after the content which did not match their learning style. The study concluded that the scores on the post-test were higher for students who received instruction matching their learning style first. However, 71% of participants were determined to be sensing learners while only 29% were intuitive learners. The authors did not discuss the possibility that studying the concrete sections before the abstract sections of content could be the more effective sequence for teaching this topic, irrespective of the students' learning styles.

A second study was conducted with 75 participants using the same AdaptLearn platform already described. In this study, one group received content which was adapted to their learning style and knowledge level while another group received content with a fixed learning path (Alshammari et al., 2015b). Participants took a survey of their perceptions of the platform after completing the course. Students who received the adaptive content gave the adaptive learning platform a higher usability score than those who received the fixed learning path, despite the fact that the user interface was the same for both groups. Students who used the adaptive version were also more likely to indicate that they would use the system again. However, it was noted that the adaptive system required greater technical support, particularly at initial setup.

In a conference proceedings paper, Stuve (2017) examines the use of the adaptive learning platform ALEKS in a college algebra course. Student satisfaction is compared to academic achievement for three groups: students using the adaptive learning platform in an online course, students using the adaptive learning platform in a face-to-face course, and those who took the course in the previous semester when ALEKS was not used. ALEKS was used to supplement an instructor-led course, either online or face-to-face, with additional practice problems. However, the paper did not discuss the number of participants, how ALEKS was integrated into the curriculum, or how the content within ALEKS was tailored to individual students.

Despite the lack of information regarding this study, its results can still prove useful. The amount of time students invested in the system, considering both number of logins and overall time spent, had a significant correlation with the students' reported satisfaction with the system (Stuve, 2017). However, only half of students felt that using ALEKS helped them earn a better grade or better understand the course material. There was no significant difference in grades between the group using ALEKS for an online course when compared to a face-to-face course, but both groups had significantly higher grades than the group that did not use ALEKS. While the satisfaction with ALEKS was low among the students who used it, open-ended questions provided valuable information for its improvement. Students indicated that the feedback explaining the material after incorrect responses was insufficient, and they also complained about the number of remedial questions after giving an incorrect answer. Stuve (2017) points out that both of these problems are relatively simple to correct.

Faculty Experiences with Adaptive Learning

All of the studies discussed thus far have been related to the learning outcomes and student perceptions of adaptive learning platforms. The relationship between faculty and the adaptive learning platforms they use can be just as important for successful implementation. This section examines adaptive learning from the perspective of the faculty who develop adaptive courses.

Phelps (2019) conducted a qualitative case study examining the process of selecting an adaptive learning platform, creating two adaptive courses, and implementing these courses. One of the adaptive courses was developed from scratch while the other was created using off-the-shelf materials from the vendor of the adaptive learning platform. Interviews were conducted with members of the project team including the project sponsor, the project manager, two instructional designers, the department leader, and two subject matter experts.

Several of the study participants, including the subject matter experts, indicated that they would have liked to be involved earlier in the process (Phelps, 2019). Most of the team members joined the project after the adaptive learning platform was selected. This contributed to a mismatch between the expected capabilities of the adaptive learning platform and its actual capabilities. This became particularly relevant for the faculty members developing a module from scratch because several of their plans could not be implemented within the system.

The vendor provided initial training to the faculty as well as guidance throughout the process of developing adaptive courses. The faculty members who participated in the initial training stated that it was too brief, vague, and not helpful for understanding the platform’s capabilities or the vendor’s design process (Phelps, 2019). Faculty members agreed that the vendor’s design process spent too much time on the early steps, including the development of personas which were never used, and did not leave enough time for building the course content and providing training to the professors who would utilize these modules in their classes. This was exasperated by the faculty’s general lack of understanding of the vendor-mediated design process. There was also a lack of clarity regarding the roles and responsibilities of the faculty versus the vendor during the design process (Phelps, 2019).

Despite the challenges faced by the design team, there were also positive experiences. The team members frequently expressed how well they came together to get the project completed despite the difficulties with pacing. Another common sentiment was the importance of having team members with diverse roles and backgrounds and including those diverse perspectives as early as possible. The participants also strongly believe in the value of adaptive learning and that belief was not diminished by their experiences (Phelps, 2019).

In addition to the case study by Phelps (2019), an interview was also conducted with a faculty member at University of Massachusetts Boston who has developed several classes which utilize adaptive learning (J. Kellinger, personal communication, April 29, 2021). This instructor uses the capabilities within the learning management system Blackboard Learn to tailor the content to the learners.

In some of her classes, students sort themselves into groups based on their personal goals. For example, in a class for people training to become teachers, the students who plan to teach science will move into one group while those who intend to teach history will move into another group. While all groups cover the same content, assignments are tailored to the specific interests of those students.

Other classes developed by this instructor are completely self-paced. These courses are built around mastery learning criteria. One of these courses is puzzle based, where students must use the course content to solve a series of related puzzles. Another is more scenario-based, where students interact with non-player characters (NPCs) and move through a sequence of events as they learn the content and demonstrate their knowledge. Blackboard only allows for a single message to be provided to students who submit incorrect answers to the puzzles and scenes encountered in these classes. To provide additional support, the instructor has also built help sections to provide additional scaffolding for students who are struggling with a task. Students can also ask questions of the instructor directly or utilize the discussion board within the Blackboard interface to discuss problems with their peers. This instructor also noted that with these self-paced courses it is important to be clear to students what they must accomplish in order to unlock the next section of the course and to explicitly state when all of the content in a section has been completed.

When asked about the challenges of managing a class where students are each at a different part of the course, the instructor stated,

> What I would love to see happen, but there are several bureaucratic barriers to this, would be just to have all of my courses be ongoing and students start when they're ready to start, and they move at their own pace, and then when they're done, they get moved on to the next course in the sequence (J. Kellinger, personal communication, April 29, 2021).

She also discussed how to conduct a class discussion of the course material when students reach the content at different times.

> They have discussion boards that they encounter as they go through and they post their responses... they respond to whoever has already posted, people respond to them, and so forth. Everyone just kind of works their way through and generate interaction that way (J. Kellinger, personal communication, April 29, 2021).

Unlike the faculty in the case study described by Phelps (2019), this instructor has created these courses with little outside technical support from the institution. Most of her knowledge of Blackboard's features has come from exploring within the platform and searching the internet for ways to implement her course designs. She also stated that very few of her students have encountered technical difficulties with her course content. This may be related to the fact that the Blackboard learning management system is used for all of the online courses offered at University of Massachusetts Boston and also used for many of the in-person courses so most students are already familiar with the basic interface.

These two scenarios demonstrate some of the wide array of experiences which faculty members can have with adaptive learning. One group selected a software platform which was specifically designed to deliver adaptive courses, worked as a team including diverse members with specific roles and responsibilities, and received support from the software vendor throughout the process. On the other hand, an individual instructor working independently used the tools at hand to add adaptivity to her courses with very little technical support. These differences and the open-ended questions used in these interviews offer a rich pool of information from which to build recommendations for other faculty who wish to incorporate adaptive learning into their courses.

Recommendations

Many examples of adaptive learning have been examined in this review. Some of these adaptive courses resulted in significantly improved learning outcomes, while others did not. The following recommendations were developed by examining the differences between successful uses of adaptive learning and those that were not.

Platform Developers and Vendors

Use Evidence to Develop Effective Adaption Models

Not all adaptive models improve learning outcomes. This was demonstrated in the study by van Klaveren et al. (2017) where practice problems with adaptive difficulty were not more effective than practice problems with a set difficulty. There is a growing body of work discussing the effectiveness of adaptive learning platforms utilizing a wide variety of adaptive models. Reviewing the literature can remove ineffective adaption models from consideration before software development even begins and direct attention toward models with a greater chance of being implemented effectively.

Secure Student Data

Student data privacy is a growing concern in education (Bloom & Attai, 2016). Adaptive learning platforms have the capacity to collect extensive data about students in the learner models including demographic information, grades, and even every click and keystroke the student makes within the system (Alshammari et al., 2015a; Hafidi & Bensebaa, 2014). It is, therefore, of utmost importance to consider what information collection is actually required to prevent over-collection and develop appropriate measures to protect that data.

Be Clear About Platform Capabilities and Design Processes

Many of the difficulties observed in the case study by Phelps (2019) were rooted in the interactions between the faculty and the platform vendor. After the software was purchased by the institution, the vendor was not sufficiently transparent about the capabilities of the platform or the development process they mediated. This led to an unnecessary time crunch at the end of the project and several last-minute design changes.

Adaptive Course Developers

Ensure Content Aligns with Learning Goals

In the study by Homer & Plass (2015), the pharmacology students' performance within the adaptive learning platform did not correlate with their performance on tests created by instructors. This indicated that the content included in the adaptive learning course did not align with the learning goals from the faculty. Similarly, in the study by Liu et al. (2017) many students did not use the adaptive learning platform for the recommended amount of time per week. One of the contributing factors for this was the lack of alignment between the adaptive learning course and the instructor-led curriculum.

These studies demonstrate the importance of aligning the content of an adaptive learning course to the learning goals. When an adaptive course is being created for a specific purpose, carefully consider the learning goals when selecting and developing content. When an adaptive learning course is developed to be used in multiple situations, it is best to allow instructors the ability to tailor the content to their own needs.

Design for Learners' Skill Level

The study by Serrano et al. (2018) and the study by van Seters et al. (2009) both examine the effectiveness of their adaptive learning platforms for learners at different skill levels. In both cases, one skill group exhibited significant learning gains while the other skill group did not. If the learners who will be taking the adaptive learning course have a wide range of expertise in the topic, include learning materials covering prerequisite topics for low-skilled students and allow high-skilled students to bypass topics they have already mastered.

Faculty and Administrators

Include Diverse Voices in Product Selection

In the case study by Phelps (2019) several faculty members expressed a desire to have been included in the process of selecting the adaptive learning platform they would use. They recommended including participants from as many roles within the educational institution as practical. A particular emphasis was made to include faculty members with low computer skills, as they would have very different questions for the vendors than those with high computer skills.

Consider how Adaptive Content will be Used

Be cautious about adding adaptive learning content on top of an established curriculum. The time required to learn a new system and troubleshoot any problems can be a distraction from the learning objectives and contribute to extraneous cognitive load (Kalyuga, 2010; Sweller et al., 1998). In addition, adding additional work on top of an existing curriculum may cause students to become overwhelmed by assignments.

It is also important to ensure that students understand the purpose of adaptive learning content within a course. Stuve (2017) and Phelps (2019) both discussed how students did not understand the purpose of the adaptive learning platform within the instructor-led courses. This correlated to low usage rates of the platforms.

Plan for Troubleshooting

Every piece of technology used in a course increases the chances that something will go wrong. Instruct students to set up their profiles in an adaptive learning platform before they need to use the software. This will allow time for troubleshooting and for students to familiarize themselves with the user interface. If your institution has a tech support staff, it may be beneficial to seek their support before introducing the adaptive learning platform to the course.

Think Outside the Box

As demonstrated by the professor from the University of Massachusetts Boston (J. Kellinger, personal communication, April 29, 2021), it may be possible to develop adaptive course content using the tools which are already available. Many web platforms and software packages include features which can be used to create adaptive content.

Future Research

The studies examined in this review predominately focus on novice learners. The *expertise reversal effect* occurs when instructional techniques that increase the learning outcomes for novices in a subject have no impact or decrease the learning outcomes for experts in a subject (Clark & Mayer, 2016). Aspects of instructional design where an expertise reversal effect have been demonstrated include the use of graphic vs. text descriptions, the level of learner control over learning paths and content, and linear vs. hypertext learning environments (Clark & Mayer, 2016; Kalyuga, 2010). As adaptive learning platforms become more sophisticated, they may be designed to modify the way that content is presented to the students based on their individual levels of expertise in addition to the existing methods of course personalization already in use (Kalyuga, 2010).

As demonstrated in this review, adaptive learning platforms vary widely with regard to which aspects of instruction they modify to create individual learning paths. It is reasonable to assume that not all methods of adaption are equally effective in all situations. Additional research should be conducted comparing the relative effectiveness of different adaption models in a variety of contexts. Such information would be extremely valuable to educators when selecting an appropriate adaptive learning platform for their specific needs.

Conclusion

Research in the field of adaptive learning is shifting from the development of algorithms needed to build the adaptive learning systems to the effectiveness of these systems in improving learning outcomes (Alshammari & Qtaish, 2019; Chen & Chang, 2015). As the body of evidence grows, it becomes possible to compare diverse studies to identify common traits of effective uses of adaptive learning in contrast to cases where implementing adaptive learning had no effect or even a detrimental effect on student learning. Based on the studies highlighted in this review, recommendations were developed for the developers and vendors of adaptive learning platforms, instructional designers creating adaptive courses, and the faculty and administrators who select adaptive learning materials and utilize them in courses. Developing and implementing adaptive learning platforms requires significantly more time and resources than developing a single course plan for all students. It is important that the design, selection, and implementation of adaptive learning is carefully considered to maximize the effectiveness of these systems, both for the benefit of the students and to ensure these resources are not spent with little benefit.

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