Maximizing the Adaptive Learning Technology Experience

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This paper explores the impact of Adaptive Learning (AL) on students and teachers who use automated grading systems to improve overall learning and effectiveness. Enhanced learning effectiveness improvements are attainable for both students and teachers with the use of Automated Grading Learning Systems (AGLS), students trained on the use of technology, become self-directed and motivated to evaluate their progress. AGLS lightens the workload for teachers with steadily increasing enrollment, allowing them to provide students with feedback that is accurate and immediate, while creating additional opportunities for positive interaction with students to reach them where they are.

ADAPTIVE TECHNOLOGY INVOLVING STUDENTS

Classroom instructors continuously seek ways to provide a more student-centered approach to meet student needs. Adaptive Learning promises to meet this need as it improves student retention, achieves better outcomes, and provides a more precise measure of student learning (Nakic, Granic, & Glavinic, 2015). Adaptive Learning has been a welcome addition to the learning environment at Colorado Technical University, a higher learning institution that provides career-oriented education by providing real world, industry-current programs in selected areas to serve the needs of students and industry for employment and career advancement. The pace of student learning varies dramatically, challenging instructors to deliver course objectives at a level each student can comprehend and retain effectively. Addressing variations in student learning is a primary goal of Adaptive Learning. Adaptive Learning enhances student learning by adjusting to students' interactions with the course material to promote mastery of the course material uniquely tailored to each student. This paper explores the impact of AL on students and teachers who use automated grading systems to improve overall learning and effectiveness.

Historical Overview

This paper explores the development and trends in adaptive learning occurring between 2001 and 2013. Nakic, Granic, & Glavinic (2015) addresses the most important characteristics of students that promote success in online learning environments. New classes of characteristics are emerging, such as learning styles, cognitive styles, and meta-cognitive abilities. Research suggests adaptive learning systems are highly effective when adapted to one or more student characteristics; learning styles, background knowledge, cognitive styles, preferences for specific learning material. Many variables influence learner differences, behavior, and learning performance; age, gender, cognitive abilities (perceptual speed, processing speed, working memory capacity, reasoning ability, verbal ability, spatial ability and other cognitive abilities), meta-cognitive abilities, psychomotor skills, personality, anxiety, emotions, learning styles, experience, background knowledge, motivation, expectations, preferences, and interaction styles (Nakic, Granic, & Glavinic, 2015).

Through Adaptive Learning Systems students work at their comfort level using technology platforms that provide different methods to enhance their learning potential. Some Adaptive Learning applications are rule-based taking students down a linear pathway while others rely on complex algorithms with multiply pathways through a collection of learning objects within the context of simulation. *Adaptivity* is different from *personalization*, its more data driven and is based on how the learner interacts with the system beyond binary responses. (Newton, Stokes, & Brian, 2015).

STUDENT READINESS/PREPARATION

Adaptive learning is an approach to instruction that utilizes technology to create a personalized learning experience for students. It is driven by a student’s behavior, interaction, aptitude, and performance. The content is adjusted based upon these factors, and the resources are attuned according to the learner’s differences. (Mahajan, 2012). Adaptive learning techniques should not be separated from traditional modes of instruction, but rather integrated with standard forms of teaching. (Baker, 2012). Adaptive learning has been explained as the application of learning using decision-making that receives ongoing feedback. (Baker, 2012). The content in adaptive learning models provides feedback and further training when the student provides an incorrect answer. The assessment of the student occurs in the sequencing of questions. This is a probability-based method whereby students with lower grades will have a higher probability of getting easier questions; as the students answer more questions correctly, the probability of the students receiving harder questions increases. Once the students near the highest score possible, they will then have the greatest possibility of being tasked with the most difficult questions. (Jonsdottir, 2015). The system also analyzes the student responses and adjusts the sequence and order of the content and skills being worked upon.

The question that follows is what fundamental skills or abilities must a student possess in order to enter an adaptive learning environment and be successful? It may seem antithetical to be concerned about whether a student is prepared for adaptive learning. After all, the purpose of adaptive learning technology is to adjust the content to the skill level of the student. Therefore, a student's competency coming into the classroom would seem to be irrelevant. However, adaptive learning technology presupposes that the student has (or has been taught) certain abilities. For example:

That the student can read and write at the level the material will be presented in the course;
That the student has the foundational education to understand the assessment materials;
That the student has the requisite test taking skills to be able to be assessed;
That the student has the ability to take responsibility for their own learning;
That the student has the requisite computer and technological skills.

Assuming that students have the foundational educational requirements to be in a particular course, we will focus on the last two points: the students need to be self-directed and technological preparation.

Preparing Students for Adaptive Learning

Through its nature as a self-centered learning process, adaptive learning creates new demands on instructors and students. There are specific areas that institutions can focus upon to prepare students for adaptive learning. Institutions must prepare students technologically and mentally. It is through the use of technology that institutions can provide personalized learning, assessment, and feedback for students (Moeller, 2011). However, the technology itself can be an obstacle to the use of technology in the classroom. In order for adaptive learning to be beneficial, the students must know how to use the technology.

Students must also be taught to develop an expansive mindset because being mentally prepared for adaptive learning means being ready for growth. Adaptive learning has the potential to help struggling students' progress more quickly and to allow gifted students to increase their knowledge base by tackling more difficult questions. When students correctly answer questions in adaptive learning environments, the questions will become more difficult. If questions are answered incorrectly, the student will be encouraged to do more practice. So students must be able to self-monitor and regulate themselves, and instructors must constantly assess and guide students through the learning process. Student motivation is a key factor in the success of adaptive learning (Baker, 2012). Students need to see results of their hard work. Struggling learners need to be motivated to work harder, and better students need the motivation to tackle more difficult problems.

An important step to ensure that students master knowledge is for the students to demonstrate their understanding of the course material. Written tests and papers provide students with the opportunity to demonstrate some of this knowledge, but certain areas of behavioral decision-making are difficult to assess using only these techniques (Baker, 2012). This is where adaptive learning methods can be effective. The data tracked by the adaptive learning technology allows instructors to know if students are putting in the effort to learn. It can also help instructors identify and motivate underachieving students.

Training Students to Use the Technology

Technology makes the adaptive learning experience possible (Moeller, 2011). Developing successful students begins with making sure the students are confident in the use of the technology. Students' experience with the use of technology varies substantially. A recent report found that among graduates preparing for the next step into higher education, 43% of students feel unprepared to use technology (Moeller, 2011.) The percentage of older students who lack technological experience is even greater. Therefore, one of the keys to successful implementation of adaptive learning is training students to use the technology.

The positive side, studies have repeatedly shown that students, regardless of age, are motivated and able to learn new technologically-based tasks (Bruder, 2014). Moreover, students can significantly increase their abilities to work with new technology with proper training (Bruder, 2014). Older students can optimize their results through extended practice (Bruder, 2014). Younger students will adapt more quickly to technological issues and learn to master the technology at an advanced rate (Bruder, 2014). Educators must also take into account the amount of time it will take users to learn to use the technology in addition to completing the course work. The more complex the technological process, the longer it will take the users to successfully master the skills. One effective assessment tool is to pre-testing students on the use of technology (Vandewaetere, 2012). The results of the pre-testing would provide insight regarding the student's proficiencies with the technological interfaces (Vandewaetere, 2012).

One of the benefits of training students in the use of technology for research, writing, and analysis is that it increases the students' skills in areas with real world applications. (Moeller, 2011). Skills in digital media, computer technology, and information processing have been identified as essential for succeeding in the current work place (Moeller, 2011). The fact that students can take the skills and apply them in the workplace could be a key motivator for many students to put in the extra work regarding learning to use the technology.

Teaching Students to be Self-Directed

In order to be successful in an adaptive learning system, students must be taught how to self-direct themselves. Studies have shown that students have more success in school when they learn self-regulatory processes (Zimmerman, 2002). Students must do more than simply react to a set of instructions. They need to be proactive in transforming their mental capabilities into action. "Self-regulation refers to self-generated thoughts, feelings, and behaviors that are oriented to attaining goals." (Zimmerman, 2002, p.65). Students self-regulate when they set clear goals and understand their own weaknesses and strengths. Self-direction requires the use of specific processes and skills, and these processes and skills can be taught. The process of self-regulation is as follows:

> Set specific goals;
> Create strategies to accomplish the goals;
> Manage the use of time effectively;
> Monitor and evaluate progress;
> Acknowledge the cause of the results;
> Develop future goals (Zimmerman, 2002, p.66).

Students need to be taught how to set goals, create a strategy to reach those goals, and learn to self-evaluate their progress. Goal setting and self-monitoring can help to compensate for differences in individual learning styles and abilities.

Enthusiasm and motivation are key components in self-direction. An increase in a student's motivation can lead to a student putting in additional work to obtaining a goal. For example, when a student answers a problem incorrectly, tools with adaptive content respond with feedback. Part of the feedback process includes encouraging students to continue to perform voluntary exercises. Therefore, it is important to understand what may motivate students to work on additional problems versus stopping.

Motivating Students

In order to be effective, adaptive learning systems must assist students in developing self-motivation. Factors that increase student motivation include educating students on what they need to do to succeed in the course, having students be active participants in the classroom, and increasing the difficulty of material as the course progresses. Another area that is motivating to students is quick feedback on their work and rewarding success (Davis, 1999).

Adaptive learning technology provides students with continuous feedback, which can affect student motivation. While ongoing feedback generally acts as positive motivation (Baker, 2012), adaptive assessments pinpoint weaknesses and require students to perform additional practice before advancing. This method of learning personalization has been used by educators throughout history. If students struggle, teachers assign them extra work so they can get in more practice and master the skill. When adaptive learning technology encourages students who struggle to do more work, it can have a potential negative effect on student motivation because one of the issues for students who struggle is the longer amount of time they must put in to get the work completed. One way that adaptive learning technology combats this issue is that the technology adapts to the level and needs of the student by providing students with questions based upon their current knowledge and grade (Baker, 2012).

However, "few beginners in a new discipline immediately derive powerful self-motivational benefits, and they may easily lose interest if they are not . . . encouraged and guided" (Zimmerman, 2002, p. 66). Thus, an important factor in student motivation is the instructor. The instructor's enthusiasm, organization, and active involvement with students plays a major role in motivating students to reach their full potential and work harder. Instructors should have high yet realistic expectations for their students, help students to set achievable goals, and provide means and methods for students to self-regulate.

Instructors should take into consideration the students existing desires and needs and provide incentives for learning. Instructors must make students active participants in the learning process.

LEARNING STYLES

On the subject of adaptive learning technologies in higher education, Liaw and Huang (2007) identified four components that should be considered in the development of such learning tools: environmental characteristics, environmental satisfaction, learning activities, and learners' characteristics. There are several learners' characteristics that have been shown, preliminarily, to moderate the efficacy of these technologies in student performance. Among the most important of these characteristics is learning style.

Learning Styles in Adaptive Learning

Recent years have seen a push for flexibility to accommodate the needs of learners in higher education through custom adaptation (Billington & Billington, 2010). Schools are under increasing pressure to reach students 'where they are'. As adaptive learning technologies proliferate through the higher education industry, the importance of learning styles to the efficacy of these technologies has been the subject of much debate. Early on in the development of higher education research, several seminal authors (Cronbach, 1957; Bloom, 1971) posited that the key to improving individualized performance is to differentiate instruction and content delivery methods, so as to accommodate the different learning styles of each student. Learning styles have been defined as "a set of cognitive, emotional, characteristic and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment" (Keefe, 1979, p. 1). According to Murray (2015), learning styles "encompass preference for information type (concrete versus abstract), presentation style (visual, auditory, or kinesthetic) and learning action (active versus reflective)" (p. 113). Learning styles themselves are thought to be the product of various other factors of individual development, including generation (Roehling, Kooi, Dykema, Quisenberry, & Vandlen, 2011; Wood, 2006).

Different adaptive learning platforms are attempting to tackle the issue of individualized learning styles with the use of different theories. Systems such as Moodle and Blackboard are attempting to accommodate the learning styles set forth by taxonomies such as Myers-Briggs Type Indicator (1998), Multiple Intelligences (Gardner, 1993), and Kolb's (1985) Learning Styles. Other systems such as iLearn are adding to this list the VARK learning style model, which is an acronym for visual, aural, read/write, and kinesthetic learning styles (Prithishkumar & Michael, 2014). According to Peter and Bacon (2010), iLearn chose to focus on VARK because the individual learning modes can be more easily mapped to course learning objectives.

Research on the Efficacy of Learning Style-Based Adaptive Learning

It stands to reason then that adaptive learning would be the ideal solution to address this issue, and yet, studies investigating the impacts of these technologies have returned mixed results. The Murray (2015) study evaluated undergraduate students in a computer literacy course. It compared approximately 100 students using adaptive learning technologies to roughly the same number using traditional modes of learning, and the results indicated that, in spite of engineering to accommodate learning style, adaptive learning platforms had very little effect on learning outcomes as compared to the alternative. Another study by Mainemelis, Boyatzis, and Kolb (2002) evaluated the performance of approximately 200 MBA students and found that there was a wide range of adaptive flexibility levels between the different learning styles present, suggesting that adaptive learning may be an effective tool for some students, but not others. A much earlier study by Stutsky and Laschinger (1995) looked at the same concept of adaptive flexibility (though obviously not in an *online* learning context) and found that there were inconsistencies between learning style classification and adaptive flexibility.

Criticisms of Learning Style-Based Adaptive Learning

Among researchers in the field of learning styles and adaptive learning, there is an alternative point of view, one of a much greater degree of skepticism concerning the propriety of expectations from these higher education tools. First, and most fundamentally, there is a good faith argument that the attempts to taxonomize learning styles in the first place have been little more than exercises in futility. This paper identified a handful of learning style theories *supra,* but Rohrer and Pashler (2012) conducted a meta-analysis of learning style research and identified a total of 71 different published theories. Yet, their review showed very little evidence for the empirical superiority of any one theory over the others. In this sense, they suggested that there appears to be a kind of 'physics envy' taking place in the world of pedagogical and andragogical study. Researchers are vying fiercely to reduce learning phenomena to labels that are just too complex, abstract, and unpredictable (as many in social sciences are) to be reduced in such a way. Rohrer and Pashler are not the only ones to argue this either (Hall, 2005; La Lopa, 2013).

Another attack on the integrity of learning style-based adaptive learning is that, even if learning styles *are* in fact legitimate classifications, the typical method of determining a student's learning style is through student questionnaires, and these, subjective instruments as they are, may be highly unreliable. Gwo-Jen, Han-Yu, Chun-Ming, & Iwen (2013) conducted a study, the aim of which was to evaluate the degree of alignment (or lack thereof) between student learning game choice and student learning style (determined through other assessment *a priori*). The results showed that students were unlikely to choose learning games which aligned with their pre-determined learning style, and thus were unlikely to experience any benefit of match between learning-style and learning tool. This is perhaps one of the biggest obstacles in mapping learning styles to adaptive learning strategy and learning objectives; if the learning style presumption is wrong at the onset, then everything that follows is likely to be a poor fit for the student.

ADAPTIVE LEARNING EFFECTIVENESS

This section will take a closer look at an aspect of Adaptive Learning (AL) which affects both the teacher and the student, the Automated Grading Learning System (AGLS). This paper is primarily focused on the student and how the AL approach improves student learning and overall effectiveness of the learning process. One of the largest areas of focus in any approach is the effectiveness of the feedback process. This feedback aspect will be discussed here in detail involving an empirical study of an AGLS.

The Need for and the Benefit of Automated Grading

With an increasing number of exercises, problems and assignments necessary for student engagement, grading by instructors is at a premium. Detailed grading gives students greater understanding of their work and allows them to correct and better understand what the concept or application is all about along with its potential use in a real-world setting. Providing students with the level of feedback they need becomes increasingly difficult as the number of students per class increases. As a result of this overwhelming work load and no seemingly good way out, professors may opt to give tests that are easier to grade but do not give the students an adequate challenge or the feedback the need to be effective learners.

Feedback Time and Quantity of Feedback Comments

In data taken from course management software it was discovered that 130 of the 429 graded assignments (30.3%) had no comments from the Professor. The days between the due date of the assignment and the time the assignment was graded and returned was on average 28 days. In cases where Professors are fortunate enough to have graduate assistants helping with the grading there could also be errors and other inconsistencies introduced into the grading of the work students submit (Ahonjemi & Karavirta, 2009). Rubrics were found to lead to much faster grading, in fact, on average the grading was 200% faster than without (Anglin, Anglin, Schumman & Kalinski, 2008). Another discovery was made as well that due to the slow time for feedback and not allowing enough time to master topic areas led to problems with students such as poor attitudes about education and a finding that overall motivation could suffer. This decrease in interest in the process could also lead to more incidents of plagiarism (Martin et al., 2007). In many adaptive learning systems, the feedback is instantaneous and the work can be repeated as many times as need for reinforcement and ultimate transfer of learning of the materials in question.

Comparison of Recommended System Versus Current Offerings

Automated Grading Learning Systems that are part of an Adaptive Learning platform could help alleviate many of the potential issues noted above. This AGLS system can be used for customized projects and be used for more than just multiple choice questions. There are applications that have been developed or are in stages of development that can accommodate the grading of case studies and other more challenging exercises without waiting on people to get the job done. This system should provide a challenging learning experience while relieving the time pressure from increased enrollment and time-intensive grading (Matthews, Janicki, He, & Patterson, (2012).

ADAPTIVE LEARNING POTENTIAL OUTCOMES

Limitations and Possible Solutions

One limitation of this study was that only one introductory computer course was involved in the testing that involved databases and the use of spreadsheets. The reason this course was chosen was to keep it simple as the only variable that was different in the research was the use of the AGLS system. This would indicate that further testing with different courses and assignments could be used to further strengthen or weaken the outcome. When using a web-designed platform such as would be used in an online course or program, the database of possible answers needs to be designed and built and as the data gathers the system would/could build on itself much like has occurred with Google. Over the years with invention, innovation and technology, Google has gotten smarter (so to speak) and it is trusted and used by almost any and every one with a smart phone or a web connection. It will take oversight to ensure that what is being shown as the correct answer is in fact correct. Quality mechanisms need to be built into the system to assure that it is to be trusted and remains effective. Obviously if the opposite occurs it would not take long before students and Professors alike would not believe in the system and lost that trust.

Future Research - Impact on Student Learning

A few of the positives for students are the opportunity to do the assignments again and over again until they achieve 100% competency/mastery. This challenges the student to use their memory to continue to refresh and further reinforce all of the lessons presented in the course. In most face to face classes it is random at best to find a Professor that properly reinforces the critical core aspects (objectives) of the lessons to the point of total recall. With the AGLS system at least there is more of a likelihood that this will occur and in the end, this is better for the student. In addition, the student is in control over when they engage in the system and how often they engage. There is no requirement to sit in a classroom and wait for the Professor to show up and hope that the Professor is of good quality and teaches to your learning style.

The future of adaptive learning models and automatic grading are being expanded to include case studies and other more subjective types of assignments. One of the challenges that are being faced currently as the study illustrated was the need to continue to improve the quality of the feedback comments. Research has indicated that the higher quality and enhancement of the feedback the higher the level of overall learning that occurs with the students. More research needs to be conducted to find better ways to enhance automated feedback.

CONCLUSION

In conclusion, achieving effective adaptive learning based on learning style relies on the flexibility and customizability of adaptive learning tools. They need to adapt enough to meet the needs of the myriad different types of learners that exist. The famous psychologist Carl Jung created the taxonomy of extroverted and introverted personality traits. However, he also asserted confidently that "such a classification is not binary, but instead, a continuum and that there is no such thing as a pure introvert or extrovert, such a person would be in the lunatic asylum" (Brainy Quote, n.d.). Similarly, we can suppose that many, if not most, learners would fall along a continuum of learning styles, as opposed to being of only one single style. Therefore, if this holds true, then the complexity of possible needs that an adaptive learning system must address increases exponentially. Markovic and Jovanovic (2012) questioned whether separate distinguishable dimensions and mutual overlaps of learning styles can be associated with a sufficient degree of certainty to even make such a task feasible. Technology has consistently provided alternative solutions that offer more interactive learning material and quality instruction to enhance the learning process. Adaptive Learning recognizes the pace of student learning varies and provides instructors with the tools needed to relieve the time pressure of increased enrollment to reach students where they are in the learning process to enhance both student and teacher effectiveness.

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