The Impact of Learning Technologies on Higher Education

CHRISTOPHER S. PENTONEY, DIANE F. HALPERN, and HEATHER A. BUTLER

Abstract

Demand for higher education has created a need for learning technologies that can accommodate the individualized needs of an increasing number of students. Thinking, learning, and memory have been studied extensively in their own right, but additional research on these topics in conjunction with advanced learning technologies is needed. Developers of computerized tutoring systems, massive online courses, and educational games will benefit from forward-thinking studies. Limitations are constantly being lifted, and research must increase in pace to ensure the integrity of upcoming learning technologies.

HOW ADVANCED LEARNING TECHNOLOGIES ARE REINVENTING HIGHER EDUCATION

If all of the hype about reinventing, redefining, revolutionizing, and reinvigorating education is to be believed, we can expect fundamental changes in how we teach and learn in the near future. Advanced learning technologies are the engine fueling change. Automated assessments, customized feedback, and gigantic online classrooms have already become reality to accommodate the growing demand for flexible learning environments and a higher education system that is more efficient, affordable, and accessible. A broad array of tools for improving the way we "do" education are being developed as advances in education and technology continuously shape each other.

As with any rapidly changing field, it can be difficult to discern the difference between substance and hype. The best of the advanced learning technologies are "created by designers who have a substantial theoretical and empirical understanding of learners, learning, and the targeted subject matter" (Aleven, Beal, & Graesser, 2013, p. 929). These new technologies offer the promise of achieving the gold standard for learning—creating deep knowledge that persists over time and transfers to new situations. The field is still in

Emerging Trends in the Social and Behavioral Sciences. Edited by Robert Scott and Stephen Kosslyn. © 2015 John Wiley & Sons, Inc. ISBN 978-1-118-90077-2.

its infancy, or perhaps toddlerhood, and thus currently offers more promise of future development than evidence.

There is a great variety of advanced learning technologies—automated assessment, personalized instruction, distance learning via proprietary platforms, massive online open courses, intelligent tutoring systems (ITSs), serious games (described later), and content-related activities such as simulations and interactive reading, to name a few. It is very challenging to design these emerging technologies, and venture capitalists are beginning to pour resources into their development with the hope of striking it rich. The excitement around the possibility of creating new and better ways of learning is a welcome change to the status quo. There are numerous research and practical issues to consider, and the hype surrounding new capabilities should be grounded in realistic expectations.

The basic model of education has remained unchanged since the time of Christ (and much earlier), who is often depicted talking to a group of people to instruct them in the ways of religion. Similarly, teachers stand before a group of students telling them what they need to know, stopping occasionally for questions and discussions, but most of the time the communication is from teacher to learner. We can now envision better ways. Rather than using a traditional classroom format, computers have the ability to adapt to hordes of individual students located around the planet. As access to the Internet becomes closer to a utility than a privilege for many people, knowledge becomes more readily available. It was not long ago when much of the world's accumulated knowledge resided on the shelves of elite libraries where only a privileged few had access. Advanced learning technologies have democratized access to knowledge, which is a huge sociological/political change that disseminates the power of knowledge more widely than ever before in history. With the speed that progress is being made, there is a need to keep the new technologies grounded in what we know about how people learn, as well as a need for high-quality research in the expanding field of technology-mediated education.

OVERVIEW OF BASIC LEARNING PRINCIPLES

Learning technologies should be informed by research that has identified best practices in instruction. Ironically, the so-called "curse of knowledge" can lead even innovative and motivated educational designers astray. This phrase refers to the commonly experienced phenomenon in which experts design systems that can only be used by other experts because they assume that a theory or skill that is well known to them will be easily grasped by novices. Rae-Dupree (2007, para. 7) describes the curse of knowledge this way, "It's why engineers design products ultimately useful only to other

engineers. It's why managers have trouble convincing the rank and file to adopt new processes. And it's why the advertising world struggles to convey commercial messages to consumers." We list here a few of the most salient learning principles that need to be considered when designing new learning technologies. An exhaustive list is beyond the scope of this essay, so we have chosen to include those that we believe offer the greatest benefits.

Present Information in a Way that Reduces Cognitive Load

One of the advantages of learning technologies is that they are able to present information to students in a variety of formats. For example, interactive e-books are capable of containing embedded videos, audio recordings, games, quizzes, interactive diagrams, and links to supplemental reading. Although there are undeniable benefits to the use of these technologies, the way in which information is presented to students affects their mastery of that knowledge. Associated ideas should be presented according to guidelines that facilitate connections in a meaningful way. Research on contiguity effects shows that when text and images are related to each other they should be placed near each other, in both space and in time (Mayer, 2009). For example, when learners have to search for mathematical diagrams associated with a formula, the demands on working memory, known as cognitive load, are increased and learning suffers (Ginns, 2006). The idea of placing related pieces of information in close proximity to each other seems like an obvious concept, but it can be easily overlooked.

Optimal learning materials involve more than visual displays. Information is better remembered when it is delivered in multiple modes, such as through auditory and visual methods combined (Mayer, 2009; Moreno & Valdez, 2005), and in multiple formats such as graphs, animations, text, and their combinations. Using varied modes of presentation enables more routes for retrieval of that information later on, and the ability to manipulate the various representations provides a level of learner engagement that would not be possible without the new technologies that support it. For example, when learners can physically manipulate kinematic graphs, they have a better understanding of the underlying principles than those who watched others manipulate the graphs (Anastopoulou, Sharples, & Baber, 2011). Management of cognitive load is vital when considering how to present information to learners.

Divide Information into Manageable Units

The contiguity principle is not the only way to reduce the cognitive load of learners. All pedagogical designs need to incorporate the fact that humans have a finite amount of working memory. Mayer and Moreno (2003) suggest that large amounts of new information be presented in discrete units to reduce cognitive load, rather than all together at the same time. Learners need to be allowed to process subunits of information before making connections between them. Furthermore, providing too much material at one time or presenting irrelevant information can be harmful to learning. Certain information and images might be visually appealing, but if they are not directly related to the topic being studied, they should be excluded (Kalyuga, Chandler, & Sweller, 1999; Mayer, 2009).

Theorists usually differentiate cognitive load into three components: intrinsic (necessary for learning), extraneous (irrelevant to learning), and germane (related to schema construction) (Sweller, van Merrienboer, & Paas, 1998). For example, if a learner is having difficulty using educational software, the additional strain associated with the operation of the software is irrelevant to the material or skills being learned. A well-designed program will have a low level of extraneous cognitive load, which means that the operation of the program (e.g., key strokes needed to manipulate graphs or the way questions are worded) is intuitive. It will also have an optimal level of germane load—the integration of information to-be-learned is neither too easy nor too difficult for the learner. These three distinctions have been supported by confirmatory factor analysis (Leppink, Paas, Van der Vleuten, Van Gog, & Van Merrienboer, 2013). It is important that the advanced learning technology not be so complicated to operate that it interferes with learning.

BOOST LEARNING WITH REPEATED RETRIEVAL

The best way to make learning "stick" is with practice that involves repeated retrieval from memory (Glass, 2009; Little, Bjork, Bjork, & Angello, 2012). The basic idea underlying the superiority of repeated retrieval of information from memory is that each item in memory has a probability associated with its likelihood of being recalled. With repeated retrieval, the memory trace is strengthened and information in memory becomes more likely to be recalled. This principle has been dubbed the "testing effect" because retrieval usually occurs in the context of a test. Broadly, findings from research on testing support giving students multiple, frequent examinations (Roediger & Karpicke, 2006). The testing effect is a well-studied phenomenon in which people retain information better by simply being tested on it. Learners benefit from testing even if they are not provided feedback on their answers to the test, but perform better yet if they *are* given feedback.

Cognitive psychologists also make a distinction between the types of retrieval, recall, or recognition. Recalling information has long been known to be more effective in learning than recognition, although recent research shows that multiple choice tests, which are recognition, can also be effective in boosting learning (Glass & Sinha, 2013; Tulving, 1967). The challenging part is identifying how to motivate students to become engaged in their own learning, so that they appreciate the need to study for recall, instead of recognition. Studying should focus on integrating or synthesizing information, rather than simply rereading or recognizing key terms. Furthermore, expectations play an important role in remembering information. Expecting to need information later makes that knowledge more accessible in the future (Szupnar, McDermott, & Roediger, 2007). This concept is related to the amount of effort viewed as sufficient in order to succeed. The effort needed for learning should be at a "desirable" level of difficulty (Bjork & Bjork, 2011) because the effort involved in learning can make recall more likely.

Lastly, frequent retrieval also makes information more likely to transfer to relevant situations (Carpenter, 2012) because the learning is deeper and recall becomes increasingly automatic. In addition, many advanced learning technologies can involve an applied setting that might improve the likelihood of transfer. For example, a serious game called Operation ARA engages students in knowledge transfer by having them identify flaws in research that have been described in newspapers, blog posts, and other everyday outlets (Halpern *et al.*, 2012). Learners compete against other players and are given immediate feedback about their performance.

PROVIDE FORMATIVE FEEDBACK

Quality feedback informs learners about why they got an item right or wrong and not just the number or percentage correct. The repeated use of testing is a feedback system; its superiority in promoting long-term learning and transfer is well documented (Carpenter, 2012). An effective learning system tests students multiple times and provides quality feedback on performance. Tests should be given according to a spaced schedule with increasing intervals. For example, space between tests could occur two days, then two weeks, and then two months after the initial learning to keep students engaged in the material throughout the learning process, rather than at a single time during the course (Glass & Sinha, 2013). Advanced learning technologies can make repeated testing easier for instructors and can provide learners with immediate feedback that explains why they got an answer wrong and what the right answer should be. Furthermore, some systems force students to reach a predetermined level of competency on a topic before they can move on to the next topics, instead of merely giving the learner feedback about their performance.

Overall, it is important to realize that leveraging technology does not necessarily mean using all available capabilities all the time. Typically, there is much to be gained from simplicity. Interfaces can easily become cluttered, which can cause distractions and overload. Certain screens, options, lessons, and feedback are going to be ideal at different times. It can be the system's task to know when those ideal situations occur. Complexity on the learner's end should increase along with the abilities of the learner, not necessarily with the abilities of technology.

IDEAL LEARNING TECHNOLOGY ATTRIBUTES

In general, the ideal learning technology will possess attributes that use the principles described, and take advantage of the consistency of computers to provide a quality environment for instruction. To be most effective, a learning technology needs to consider learning research in its design. We already have the ability to store large amounts of data about individual learners, including rates of reading, response latencies, errors they make for each learning objective, level of engagement, length of responses to open-ended questions, and much more. By combining data mining with education research, it is possible for a system to predict students' scores on future exams and identify areas in which each student or group of students needs more instruction or feedback. People learn at different rates, and the ideal solution is for teachers to assess these needs, and make adjustments accordingly. The usual response to a wide range of learning abilities and rates in a large classroom is to teach to the hypothetical average student, a procedure that tends to lose both the exceptionally talented and exceptionally slow learners. By automating this process, all students can be instructed at their own level of understanding at the same time, together or separately.

Educational data mining is a fast growing academic field. It is also becoming a popular approach to everyday living with "quantified life" advocates urging people to keep careful quantified records of all aspects of their lives so that they can discern health patterns, learn more efficiently, and achieve almost any goal in their lives. Furthermore, relevant feedback can be given at appropriate times in order to facilitate learning and catch errors, allowing a computerized program to recalibrate the level of instruction for each student. One such program, SuperMemo (Wolf, 2008), is designed to assess when students achieve a 90% probability of recall, and then queries the students with appropriate questions as a way of increasing retrieval strength. We expect that the personalization of learning experiences is an emerging trend that will yield high gains in learning, especially if students are monitored correctly. Learning technologies need to personalize instruction by taking into account individual needs from student-generated data. Automated personalization is one of the most hyped capabilities of computers in education. A good system will help students overcome difficulties and frustrations often associated with learning, such as short attention spans and learning materials that are based on faulty assumptions about what learners already know. Advanced learning technologies should be able to flag misconceptions for each learner and provide specifically targeted materials designed to correct the misconceptions.

It is every professor's dream-no more essay grading. Programs that offer automatic analysis of essays are likely to be "the next big thing," if (and it is a big if) these grading programs can demonstrate that they are reliable and valid, and users can get over the prejudicial belief that humans are inherently superior at this task. At this time, automated grading systems are far from perfect, but many are as reliable as having two human experts grade essays (Graesser & McNamara, 2012). These programs are still poor at recognizing novel metaphors, irony, sarcasm, and highly unusual high-quality responses, but we suspect that the same can be said for human graders. There are many automated grading systems, each designed with a particular specialization. One of the best analyzes content using Latent Semantic Analysis (LSA, Landauer McNamara, Dennis, & Kintsch, 2007). The underlying principles are complex, but rest on an analysis of the number of adjacent and nearby words that are found in natural language, a process known as *n*-gram analysis. Automated grading systems are already being used in high stakes testing (e.g., the writing assessment portion of the Graduate Management Admission Test), and based on their successful use in this context, we believe that automated grading will soon be more widely available for general educational use.

Advanced learning technologies can require students to respond in meaningful ways as they learn. There are programs that monitor student emotions during a learning session. For example, Linguistic Inquiry Word Count (LIWC) designed by Pennebaker and his colleagues (Chung & Pennebaker, 2007; Pennebaker, Mehl, & Niederhoffer, 2003) can detect negative and positive emotions, so these sorts of programs could be used to screen for mental health problems and for engagement in learning. Other programs can detect when learners are bored and/or frustrated and can alter the learning materials in ways that increase engagement (D'Mello & Graesser, 2012).

Although it is impressive that affect can be automatically monitored, positive interpersonal connections that often result between learners and their teachers need to be maintained as we move increasingly toward computer-mediated learning. Ask people about their favorite teacher and you are likely to get a glowing response about the role that a special teacher

played in the respondent's life. There are intangibles in the teacher–learning interaction that can create strong bonds and change the trajectory of the student's life. As we inevitably move into the use of advanced learning technologies, we want to find ways to maintain that special relationship. Advanced learning technologies can support and enhance small-class seminars in which each student responds to the teacher's prompts, often in real time. It remains to be seen if the same sort of relationship can be fostered as we redefine terms like "live instruction" and "distance learning." We believe that it will be possible to create strong, positive student-teacher bonds and that with careful design we can see more of these relationships develop, but of course, we will not know until we have high quality programs designed with this purpose in mind and enough data to support a conclusion.

Perhaps the most socially influential factors of an ideal system are the considerations of legitimacy and cost. Certificates of completion or some indicator of learning are becoming very important. Grades are given in traditional courses, and degrees or diplomas are earned when certain requirements have been met. Having tangible evidence of completion of a learning program is not only motivating for learners, but is an indication of legitimacy. Many free online courses offer some type of evidence of completion already, and will continue to do so as online education increases in popularity. However, keeping such systems cost-efficient can be a struggle.

Costs are always a focus for cash-strapped universities and even their more affluent counterparts. A good learning technology must be a fiscally sound investment. The benefits from a system must be worth the cost of implementation and upkeep. Luckily, the quick developmental pace of hardware has permitted better accessibility and lower cost. Considerations of cost become more vital as the learning platform becomes larger and more complex, and when changes to the platform and technical support are a bigger task.

THE CAPABILITIES OF LEARNING TECHNOLOGIES

Many impressive technologies exist, but more research is needed to utilize their educational potential. Three major areas of learning technology have surfaced and gained solid traction recently: ITSs, serious games, and Massive Online Open Classrooms (MOOCs). These tools have been in constant development for some time, but technological advancements are quickly making them all much more effective.

INTELLIGENT TUTORING SYSTEMS AND PERSONALIZED INSTRUCTION

Emerging from the popularity of Big Data, which involves gathering, storing, and analyzing large amounts of constantly changing information,

automated assessment of student performance now allows for efficient personalized instruction. By combining the disciplines of data mining and computer science with pedagogy, learning systems can automatically make adjustments to assist in student learning. ITSs are computerized learning environments that are able to adapt to the differing needs of individuals and provide appropriate feedback. Effectiveness of ITSs is an extensive area of research, with several interesting findings that could guide further studies.

In a meta-analysis of 34 independent samples from 26 different studies conducted between 1997 and 2011, Steenbergen-Hu and Cooper (2013) found that ITSs were at *least* as effective as regular classroom instruction for learning mathematics at the K-12 level, and possibly slightly better in some cases. Positive learning effects were found to be greater for students from the general population, as opposed to low achievers, suggesting that there may be some minimal level of basic knowledge, skills, and motivation that are important for computerized learning. Finally, the analysis also found that interventions lasting longer than a year typically showed weaker effects than those lasting less than a year. Steenbergen-Hu and Cooper offer a few interpretations of this counterintuitive finding. Motivation may be lost as novelty wears off, researcher control over the implementation may have varied between short and long interventions, or the studies themselves may have differed in robustness of methods.

Other studies involving adaptive learning technologies have shown benefits to student learning. Walkington (2013) tested the effect of personalizing the context in which math problems were presented on student ability to write out algebraic equations. Students took a survey that assessed their interests, and were then presented with math problems that were either personalized to those outside interests, or were normal word problems. Students who received personalized instruction demonstrated better performance on both types of problems. That is, students who learned in a context in which they were interested were better able to express those problems and later problems in equation form than were students who learned in a non-personalized context. It is likely that a familiar or interesting context provides students a scaffold in which to frame the math problems.

It should also be noted that different ITSs vary in the specific capabilities they have, and the quality of their feedback. There are almost a limitless number of variables to be studied. As education becomes more advanced, automated learning systems become an even more promising area of research. Success from these learning systems has paved the way for larger, more extensive platforms that can handle more than just personalization of instruction to individual students.

$S_{\text{ERIOUS}} \; G_{\text{AMES}}$

It has as long been a goal of educational technology to take advantage of the immersion and challenge inherent in games. There is something very attractive about the combination of fun and learning which can be difficult to make a reality. Serious games have already been shown to be effective in teaching materials such as scientific thinking (Halpern *et al.*, 2012). Games have the ability to get learners involved with the material, and promote an active role in learning. They go beyond simple presentation of knowledge to get students engaged in learning subject matter.

Games can make use of an imaginary, engaging context for students to frame material. Instead of being bystanders in a passive learning process, students can become an active part of an adventure in which they play an exciting and meaningful role. Outcomes do not always have to be the same—they can be dependent upon learner performance within the game. Dynamic content is a great channel through which to give learners feedback. With games, feedback is a natural part of the process that will assist students as long as they are attempting to perform well.

A recent meta-analysis of serious games found that game players learned more and had better retention of the information they learned compared to students who learned in a conventional learning method (Wouters, van Nimwegan, van Oostendorp, & van der Spek, 2013). Surprisingly, the learners who played the games were not more motivated to learn. We believe that this result is caused by the constant need to use high-level engagement in learning games. Students pay attention and often spend more time on the task of learning when engaged in games. The best games target deep learning as the intended outcome, and deep learning is difficult work.

Mini games are also becoming popular. These games tend to be shorter, web-based, and teach a single topic. Teaching simple concepts does not require a full-fledged game, so independent developers can create mini games more readily. These types of games are also inherently modular, so they can be presented alongside associated material at any point. For example, one of the authors of this chapter routinely uses a mini game in her statistics classes (WISE, 2014). She plans out her lesson plan for a particular topic (e.g., confidence intervals), and uses a small web-based game to supplement the material presented in class. Students can manipulate graphs and data until they understand the concept, and they can revisit the website as often as they like. Students also get involved building these mini games, which deepens their understanding of the material considerably.

MOOCs (MASSIVE ONLINE OPEN CLASSROOMS)

With the advent of MOOCs, the Internet has created pathways for amazing opportunities that would not have been feasible a decade ago. Hundreds of thousands of students can now enroll and participate in a single, open course. Once these courses have been developed and designed, much of the process can be automated. Although the completion rates and student performance may not be as high as traditional coursework, identifying factors that can better motivate learners to complete these courses is an interesting applied research area. One study found that the highest completion rate was 19%, with many showing extremely low rates (Koutropoulos *et al.*, 2012). With such large sample sizes, there are huge amounts of data available to be mined on the behaviors of students who enroll in this type of online course.

People who register for free online courses will have different goals and expectations than students who enroll in traditional college courses. Undoubtedly, there is interest even from learners who do not complete the courses. Investigating retention rates based on individual profiles is a promising area where data mining should be used for initial insight. Specific hypotheses for further research can inform these increasingly popular learning environments. In a recent systematic review of published research articles about MOOCS, the authors concluded that the number of MOOCs and research publications are increasing rapidly (Liyanagunawardena, Adams, & Williams, 2013). Extrapolating from these data, we can expect much more research on MOOCS in the next decade.

LEARNING WITH TECHNOLOGY IS THE FUTURE

The days of information being confined to libraries and a few well-read minds have disappeared. Knowledge is now readily available to anyone with an Internet connection, but effective methods of disseminating this knowledge still need to be perfected. Several challenges exist for advanced learning technologies. Research on learner intentions, motivations, and other factors will assist in advancing best practices for new technologies. The most current influential trends leverage the adaptability of technology, focusing on accessible, individualized learning. Personalized lessons that can be taken anywhere in the world are the future of learning technologies, but more research is needed to make them most effective. Much of the infrastructure and technical capabilities already exist, but behavioral research will need to hasten its pace if it wants to match the speed that these innovative technologies are being produced. Research on these systems is being undertaken and much more is still needed to ensure that these technologies are effective and can meet the demands of our students.

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CHRISTOPHER S. PENTONEY SHORT BIOGRAPHY

Christopher S. Pentoney is a graduate student in Applied Cognitive Psychology at Claremont Graduate University. His research interests are in the application of statistics and data mining in learning technologies. His current projects involve the development of learning software for statistics, and automating the classification of simple and difficult text.

DIANE F. HALPERN SHORT BIOGRAPHY

Diane F. Halpern is the Dean of Social Sciences at the Minerva Schools at KGI. She is past president of the American Psychological Association. Diane has published over 20 books including, Thought and Knowledge: An Introduction to Critical Thinking (5th ed.) and Sex Differences in Cognitive Abilities (4th ed.). Diane's recent projects include the development of Operation ARA, a computerized game that teaches critical thinking and scientific reasoning (with Keith Millis and Art Graesser) and the Halpern Critical Thinking Assessment (Schuhfried Publishers) that uses multiple response formats, which allow test takers to demonstrate their ability to think about everyday topics using both constructed response and recognition formats.

HEATHER A. BUTLER SHORT BIOGRAPHY

Heather A. Butler is an assistant professor in the psychology department at California State University Dominguez Hills. She has a number of research interests that are grounded in human cognition (critical thinking, advanced learning technologies, cognitive bias in the legal system). As a graduate student, Heather was involved in the development Operation ARA, a serious game that teaches scientific reasoning. She is currently pursuing grant funding to develop a new serious game that would improve the critical thinking skills of college students.

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