# Crossing Disciplinary Boundaries to Improve Technology Rich Learning Environments

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Abstract

This paper describes technology rich learning environments (TRE) that use a combination of tools to support learners. A review of the learning metaphors that guide the design of cognitive, metacognitive and affective tools is presented. Adaptive technologies are discussed in the context of the Learning Environments Across Disciplines (LEADS) Partnership that examines the co-occurrence of affect and emotion while learning with technology. Convergent methodologies are used to identify how students think and feel in these contexts. Examples of specific TREs will be discussed in terms of the theories and methods used to provide evidence of what learners know, feel, and understand.

# Crossing Disciplinary Boundaries to Improve Technology Rich Learning Environments

There is a long and rich history of adaptive technologies designed to improve teaching and learning. Rather than review this history, this paper addresses specific technology tools created to support learning. Learning "tools" are as commonplace as the alphabet and numerical systems created to represent, communicate and process information (Nickerson, 2005). The printing press and the World Wide Web were both considered technological innovations for distributing and sharing information (Lajoie, 2007; Lesgold, 2000). Cognitive tools are technology tools that allow learners to engage in higher order thinking skills by supporting lower level skills, offering opportunities for generating, testing and evaluating hypotheses in problem solving contexts, and scaffolding memory and metacognitive skills (Jonassen & Reeves, 1996; Lajoie, 2005, Salomon, Perkins & Globerson 1991).

This paper will describe technology rich learning environments (TREs) that use a combination of tools to support learners. TREs have an instructional purpose and are guided by learning theories to support learners in achieving the goals of instruction (Lajoie & Azevedo, 2006). These affordances include opportunities for learners to interact with instructional materials; receive feedback through the structure of the environment and/or by human or computer agents that scaffold the learner; and present adaptive challenges to sustain attention and keep learners engaged. Our challenge is to create such adaptive learning environments that teach 21st century skills and accurately assess student mastery of these skills, a skillset that emphasizes, but is not limited to critical thinking and problem solving, creativity and innovation, collaboration, self-direction, and digital literacy.

**Cognitive Tools: Variations On a Theme**

Metaphors have been used to guide and describe theory and research pertaining to learning and instruction. Mayer (1996)'s seminal article describes the evolution of learning theories moving from behaviorist to information processing to constructivist approaches to describe learning and instructional practices based on such theories. The metaphor guiding the behaviorist movement was that of response strengthening (the law of exercise, Thorndike, 1911, 1965) where learning is strengthened through stimulus response methods that result in instruction that consists of drills and practice. The information processing metaphor proposes intervening variables where information is encoded, structured, stored and retrieved by the learner (Neisser, 1967). From an instructional perspective Mayer explains that the information processing metaphor is sometimes seen as knowledge transmission through mediums such as lectures and books. However, he further explains that the concept of knowledge acquisition grew with the introduction of the computer in the 1950s where the leap was made to the mind as computer where information is received and transformed in some manner (Lachman, Lachman & Butterfield, 1979). In other words, knowledge is not simply received but constructed in some fashion. Constructivism remains the current learning metaphor where learners make sense of the information they receive by constructing their own knowledge through guided discovery, discussion etc. In essence, learners are situated in meaningful learning experiences where they learn through building their own understanding (Greeno, 1998). However, this metaphor has been stretched to include the social-constructivist notion of learning where we learn from others by sharing multiple perspectives (Anderson, Greeno, Reder, & Simon, 2000; Clancey, 1997; Vosniadou, 2007,von Glaserfeld, 1995)

Metaphors for learning with technology are also used to guide research on adaptive technologies. The likelihood of technology fostering learning is greatly increased when cognitive theories guide the design of technology for instructional purposes (Lajoie, 2005). The cognitive tools metaphor is used to describe how technology can support learning by helping learners accomplish cognitive tasks (Jonassen & Reeves, 1996; Lajoie & Derry, 1993; Lajoie, 2000; Perkins, 1985; Salomon, Perkins, & Globerson, 1991). Cognitive tools can be used to assist memory, problem solving, decision-making, metacognition, etc. Computers can serve as intellectual partners (Salomon, et al., 1991) by helping learners accomplish tasks through the sharing of information. Sharing, in this context, means that the computer can assist the learner in some way in solving problems. Intelligent tutoring systems and the advent of pedagogical agents and multi-agent computer based learning environments demonstrate how far the notion of computers as partners has evolved. These tutors and pedagogical agents now serve learners by providing assistance in the context of their learning. The field of computer supported collaborative learning also reflects the shared partnerships between groups of learners and technology tools. Cognitive tools, be they simulations, games or intelligent adaptive systems, can be created to help learners generate and test hypotheses in the context of complex problem solving which ultimately helps them construct new knowledge and practice the application of knowledge in the context of meaningful activities.

The cognitive tools metaphor has evolved together with theories of learning and the last three decades have had different questions driving the design of adaptive technology. In the early 90's researchers were preoccupied with the question "can we model human problem solving using technology" and three camps formed: modelers, non-modelers and middle camp (Derry and Lajoie, 1993). Researchers in the model camp studied performance to see how experts differed from novices. They would then develop intelligent computer tutoring systems that would use models of learning to automatically diagnose errors and adapt levels of feedback based on an individual's performance. The non-modelers thought it impossible for computers to diagnose all human errors and envisioned the use of technology as a cognitive tool to situate experiences for learners in authentic contexts. Instead of modeling the learner, they used technology to support the social experience by acting to scaffold learners, a pedagogical process whereby knowledgeable students help learners to perform tasks that they cannot do by themselves (Wood et al., 1976). Scaffolding allows learners to realize their potential by providing assistance when needed and slowly removing it as learning occurs (Collins et al, 1989; Lajoie, 2005, Pea, 2004; Vygotsky, 1978). Finally, the middle camp combined cognitive apprenticeship, constructivist learning, and cognitive tools with computer-based student modeling. This last camp adheres to the belief that computers can and should serve the cognitive mentorship function, providing scaffolding without giving over control of the learning/assessment process to those using the system.

In the following decade, as learning theories reflected constructivist designs, researchers started to consider the influence of both the individual and the social context of learning, and asked, “Who should we model” the individual, the group or both? The debate resulted in an evolution of theory where both the individual and social construction of knowledge was taken into consideration (Anderson, et al., 2000). Researchers demonstrated the value in modeling both individual knowledge construction and learning in social situations through the use of technology. Computer, human tutors, and peers were considered as assisting in the modeling of knowledge and scaffolding learners in the context of problem solving.

This decade we face a different question, pushing the cognitive tools metaphor further. The question is “what should we model?” Research on learning and affect is becoming more connected and consequently there is more interest in adapting instruction to differences in learners’ cognitive skills and affective inclinations to help them reach their potential. Adaptive tools for cognition (how we think, remember, decide, perceive, understand and use knowledge) need to be examined in conjunction with how affect (enjoyment, interest, achievement emotion, etc.) is affected in specific learning situations. Affect can increase or decrease learning and retention depending on the context. Positive affect is usually associated with engagement and interest in learning whereas negative affect can lead to disengagement. In addressing the affective component of learning, it is important to recognize how affect influences decision-making and how individuals are engaged as they interact with new technologies. The current metaphor for learning with technology must extend the computers as cognitive tools metaphor by contributing to theories and methodologies that model both the cognitive and affective processes that lead to effective learning and engagement for individuals and groups of learners.

In the section below we discuss how the expanded views of learning with technology have led to more effective designs for adaptive learning environments. In line with contemporary theories of learning and instruction, the metaphor of computers designed as tools to augment human cognition has broadened in terms of the breadth and depth of constructs that are targeted, including affective and motivational activities that impact learning as well as self-regulatory processes that mediate this relationship.

**Broadening the Scope of the Metaphor: Affective Tools for Learning**

The old adage "where there is a will there is a way" is historically grounded in psychological theories (James, 1899) where the will to do something was linked to action. There is an obvious connection between the will to act and the motivation to learn that pertains to where the locus of control of the learning situation resides (Bandura, 1977). Pekrun's (2006) control value theory expands on these assumptions, stating that when an individual feels in control of their situation and values the activity more positive learning outcomes can occur. However, there is a complex relationship between learner control and appropriate levels of challenge. Lepper (1988) cautions that unconstrained learner control might lead to the selection of activities that are too challenging which could lead to failure or alternatively selecting tasks that are too easy can lead to boredom. Volition, the will to do something, plays a strong part in self-regulated learning processes that require the control of monitoring, evaluating, and revising ones learning strategies (Corno, 2001).

Azevedo and Feyzi Behnagh (2010) caution that dsyregulation may occur in TRE situations that are too open ended since learners may not have the SRL skills necessary to distinguish what is important for learning in such situations (Kirschner, Sweller, & Clark, 2006; Hmelo-Silver, Duncan, & Chinn, 2007).

When expanding our ideas about how to develop affective tools for learning we need to identify how adaptive learning environments provide learners with motivationally appropriate learning environments (Du Boulay, Avramides, Luckin, Martinez-Miron, Rebolledo Mendez, & Carr, 2010) that contribute to positive emotions, engage students in persisting in their learning.  As students learn with technology the relationship between emotion, effort, persistence, and learning can be done in a more temporal manner, in that student emotions can be monitored dynamically while learning. Analyzing emotion in the context of learning with TREs can help determine the precursors to both positive and negative learning situations.

**Deepening the Scope of the Metaphor: Metacognitive Tools for Learning**

The field of metacognition and self-regulated learning continues to evolve and part of this evolution has been to provide operational definitions of constructs in this area that others can agree to (Dinsmore, Alexander & Loughlin, 2008; Lajoie, 2008). A recent handbook on metacognition and learning technologies (Azevedo & Aleven, 2013) demonstrates how far researchers have broadened the metacognitive tools metaphor to assist learners using technology. As we start to examine  “self” and “other” regulation more broadly, careful considerations of operational definitions and methodologies are needed calibrate the research. Furthermore, new links must be made to the social-emotional variables that influence metacognition in individuals and groups of learners.

Metacognition refers to thinking about one's own thinking (Flavell, 1979). There is both metacognitive knowledge and regulatory mechanisms needed to help one determine what one knows and understands (Baker & Brown, 1984). Self-regulation can be applied to many contexts and involves cognitions, behaviors, emotions and motivations (Bandura, 1977; Loyens, Magda, & Rikers, 2008). Individuals use cognitive and metacognitive regulatory processes to plan, perform, and maintain their desired objectives (Volet, Vauras, Khosa, & Iiskala, 2013). Self-regulation serves a purpose in academia, in that it can be applied to learning, and hence the term self-regulated learning (SRL) was formed (Corno & Mandinach, 1983; Zimmerman, 1986) referring to monitoring and controlling ones' own learning (Dinsmore et al., 2008; Lajoie, 2008; Pintrich 2000, 2004; Zimmerman & Schunk, 2001). Self-regulated learners can actively manage their own learning cognitively, motivationally, and behaviorally (Azevedo, 2009; Winne & Perry, 2000; Zimmerman, 2008). SRL is a recursive process that occurs at all stages of a learning episode. Some refer to SRL as an event that unfolds dynamically where individual SRL processes fluctuate in terms of frequency during the learning task (Azevedo, Moos, Johnson, & Chauncey 2010).

## Learning and Instruction: What are the Affordances of Technology?

The underlying mechanisms and design principles that dictate how learning and engagement is enhanced in the context of TREs have been the focus of continued research during the last decade. Although generalizable guidelines are still a matter of considerable debate, most learning scientists now agree that technology promotes learning and engagement while instruction (1) conveys opportunities for one-on-one tutoring with pedagogical agents, (2) externalizes models of proficiency in task performance, (3) enables sustained practice in performing meaningful tasks, and (4) supports learners while they become more autonomous and self-directed.

**Learning from Human and Computer Tutors or Agents**

There is no “one-size fits all” when it comes to instruction. Individuals differ in their aptitudes, and in their motivational profiles and consequently have different preferences for learning. Consequently, it is no surprise that one-on-one tutoring with good tutors is the most effective form of instruction since tutors can adapt their instruction based on the learner’s needs. Bloom (1984) reported that students involved in "one-to-one tutoring," with human tutors, performed around the 98th percentile, 2 standard deviations above those in traditional classrooms. Tutors help learners by establishing models of competency within specific domains that can help those less competent become more proficient (Lajoie, 2003; Pellegrino, et al., 2001).

Research using intelligent tutoring systems have shown improvements over typical classroom instruction in several disciplines, including mathematics (e.g., Cognitive Tutors; Koedinger & Corbett, 2006), computer science (e.g., Constraint-Based Tutors; Mitrovic, Mayo, Suraweera, & Martin, 2001), microbiology (e.g., Narrative-Based Tutors; Rowe, Shores, Mott, & Lester, 2011), as well as physics and computer literacy (e.g., Dialogue-Based Tutors; Graesser, VanLehn, Rose, Jordan, & Harter, 2001). Targeted approaches to scaffolding specific SRL processes have also been conducted using animated pedagogical agents embedded in TREs for science learners (Azevedo, Cromley, Moos, Greene, & Winters, 2011). Multi-pedagogical agent environments are providing feedback for specific learning skills that provide similar tutoring advantages.

**Learning from Models of Performance and Competence**

Studies of expertise demonstrate that proficiency is achieved through deliberate practice of target skills with feedback (Ericsson, Krampe & Tesch-Romer, 1993). TREs can help learners deliberately practice skills with appropriate scaffolding- a pedagogical process experts use to help learners perform tasks they cannot do by themselves. Scaffolding can be a cognitive support for problem solving or motivational support to help learners realize their potential (D'Mello & Graesser, 2012). As students become competent and confident, scaffolding eases away so that students become independent learners (Azevedo & Hadwin, 2005; Lajoie 2005; Pea 2004). When activities are too difficult for learners to do alone, experts (human or computer) can model skills to help learners perform a task efficiently (Bandura, 1977; Lajoie, 2007; Zimmerman, 2008). Using technology to assist learners along their individual learning trajectory with appropriate scaffolds can help them achieve learning goals that they would be incapable of without such assistance. There are several mechanisms used to establish such models. One is to identify the cognitive competencies needed to solve the task at hand so that the learners' model of performance on the task can be compared to the competencies that need to be acquired. Understanding superior human scaffolding can lead to better models of computer scaffolding. TREs can be designed with different models of human and computer tutoring.

**Learning Through Interaction**

Technology can provide learners with opportunities to interact with real world problems and can serve as “learning partners” that form the basis for interaction. Learning partnerships involve interaction with others (e.g., tutors, teachers, real or virtual peers, computers, books, and media). Learners’ experiences can be supported by technology and situated in the context in which one is working and includes the people, the tasks, and the tools that are available to help perform that task (von Glaserfeld, 1995). Situated learning theories describe human thought and action in response to how complex environments provide opportunities for integrating information from multiple sources and promote the social construction of knowledge (Clancey, 1997; Greeno, 1998). Understanding the mechanisms of human-human tutorial dialogue can assist in the design of natural language tutorial dialogue systems in TREs. Lester and colleagues use computer and cognitive science methodologies to explore these issues, such as (a) how learner characteristics influence the structure of tutorial dialogue, (b) how human tutors balance cognitive and motivational scaffolding, and (c) how these variables impact learning and self-efficacy gains (Lester, Rowe, & Mott, 2013).

**Learning Through Meaningful Tasks**

Learners are typically more engaged in their learning efforts if they value the activity and if they feel in control of their learning (Pekrun, 2006). According to Pekrun’s (2006) control-value theory, emotions that individuals experience during learning activities are determinants of learning success. Technology provides a tool for self-directed inquiry, whereas Weimer (2010) asserted that traditional educational contexts promote dependency because so much of it is outside students' control – from the selection of content, to in-class activities, to participation and assessment. This leaves little time and opportunity for students to develop independent study habits and higher-order cognitive skills. When learners demonstrate or articulate their ability to do a task on their own then scaffolding can be faded and eventually removed. A major goal of instruction is that *students must learn to learn* and become self-regulated learners (Zimmerman, 1986). Advanced learning technologies can foster students' SRL processes that lead them to attain their learning goals. Azevedo and colleagues (Azevedo, Moos, Greene, Winters, & Cromley, 2008; Azevedo, Harley, Trevors, Duffy, Feyzi Behnagh, Bouchet, & Landis, 2013; Azevedo, Johnson, Chauncey, & Burkett, 2010) examine the relationship between scaffolding and SRL in science and demonstrate how to scaffold learners to become independent, and capable of monitoring and controlling their own performance.

## Assessing Learning and Engagement with Technology

The Learning Environments Across Disciplines (LEADS) Partnership was created to advance our understanding of how theories can influence the design of better learning opportunities with TREs (see www.leadspartnership.ca). In particular, we expand our examination of learning to include the co-occurrence of affect and emotion while learning to determine their influence on student outcomes. We use an interdisciplinary approach to design and assess learning with TREs. Educators, psychologists, computer scientists, engineers, physicians, historians work in tandem to examine the complex relationship between cognition, metacognition, behavior, motivation and affect while learning with technology. We study engagement in schools, from middle school to university. The interdisciplinary approach allows us to pose new theoretical frameworks as well as test methodological innovations in providing evidence of learning and engagement with TREs. Convergent methodologies are used to identify how students think and feel in these contexts. Such methods include computational analyses, machine learning, semantic analysis, and physiological and behavioral indices. The TREs include simulations, intelligent tutoring systems and multimedia learning environments, agent based systems, augmented reality systems, and serious games. We provide a few examples of how TREs can determine when learners are *engaged* and happy as opposed to bored and angry while learning. Our goal is to discover how best to tailor the learning experience to the cognitive and affective needs of the learner. Examples of specific TREs that use this integrated approach are described below in terms of the theories and methods used to provide evidence of what learners know, feel, and understand.

New assessment designs and methods are needed to examine the ways in which students learn using TREs. In particular, advanced technologies for learning are able to address 21st century skills (i.e., inquiry, problem solving, communication) in ways that were not conceivable with standardized achievement tests. Shute, Leighton, Jang & Chu (under review) describe how technology is changing assessment due to its dynamic and adaptive nature. Most importantly they discuss the need for more attention to the intersection of cognition and emotional variables, and better attention to the types of tools that promote and evaluate learning.

In order for a technology to be adaptive it must monitor and update a student's model of performance or proficiency. Individuals differ in their levels and types of competencies and the rate in which they make improvements over time. Adaptive feedback helps learners along a learning trajectory by using learner profiles to reveal areas where they need assistance. Innovative forms of assessment lead to informed decisions regarding adaptive feedback.

Adaptive instructional systems may be defined as a systematic process which consists of four steps: (1) capturing information about the learner; (2) analyzing learner interactions through a model of learner characteristics in relation to the domain; (3) selecting the appropriate instructional content and resources; and (4) delivering the content to the learner (Shute & Zapata-Rivera, 2012). The analytical function of the learner model can be further classified in terms of processes conducted at both the macro and micro levels (VanLehn, 2006). At the macro-level, a representation of the path towards competency within the domain is updated for each task with the aim of selecting the next task that is the most appropriate for the learner. At the micro-level, instructional materials such as hints and feedback are delivered to the learner on the basis of the learner model that is repeatedly updated over the duration of task performance.

Adaptive technologies generally use at least one form of assessment that is embedded in the learning environment. Embedded assessments are both dynamic and diagnostic (Lajoie & Lesgold, 1992) and can lead to better learning opportunities. An important development in assessment design is the use of learner evidence collected by the system to build complex multidimensional profiles that can be extracted from the data (Shute et al., under review). Evidence of cognitive, metacognitive and affective signatures can be identified both separately and in combination so that we can see when a learner is engaged, disengaged, reflecting or not reflecting on their own learning.  Furthermore, many researchers are using a combination of assessments to build a more robust and nuanced assessment of learner profiles during specific learning situations.  One such assessment is referred to as stealth assessment (Shute, 2008) whereby a learner is assessed during "game play" in a seamless manner not realizing that they are being assessed at all.   We describe this approach below in the section on Newton's Playground, a physics game, where learners are assessed in the context of playing a game and learning physics.

**Learning Physics through Game Play: Newton's Playground**

As stated earlier, learning through interaction is one of the most meaningful types of learning since learners are situated in an active learning environment doing some thing rather then simply absorbing material that is transmitted. Shute and colleagues (Shute, Ventura, & Kim, 2013) created Newton's Playground as a game where learners play with physics concepts by interacting with materials to test their theories about gravity and force. Players create physical objects to solve physics problems. These objects  "come to life" in the game when drawn (e.g., levers, ramps, pendulums) and they obey basic rules of physics (e.g., Newton's three laws of motion). In this way learners test their hypotheses about laws of motion by playing with objects.  Stealth assessment of learners occurs as they play their game. Data are collected during the course of gameplay, and ongoing assessments are used to generate appropriate levels of feedback based on the learner activity (Shute, 2008).

Stealth assessment is evidence-centered (Mislevy, Steinberg, Breyer, Almond, & Johnson, 2002) where inferences are made about learner competencies through their actions that are recorded and updated in TRE profiles (Conati et al., 2002). Shute examines how learning competencies are acquired in the context of games so they can be exploited to support learning processes and outcomes (e.g., causal reasoning, creative problem solving, physics understanding). Games can then be designed to sustain attention by providing optimal challenges to learners. As stated earlier, appropriate motivational designs are needed to keep learners engaged in the learning process. Optimal learning challenges are those that hover at the boundary of a student's competence (Gee, 2005; Cordova & Lepper, 1996; Vygotsky, 1978).

Some TREs can be thought of as one-stop-shopping where one environment can provide the learner with all of the materials they need to enhance their learning. For instance, Shute, et al. (under review) describe how TRES can provide opportunities for problem solving, information searches, discriminating and synthesizing multiple information streams and data sources, planning, modifying and re-executing strategies, hypothesizing about consequences to best actions, testing ideas, receiving feedback directly, perseverance, cognitive flexibility creativity and coordinating and collaborating with others. The challenge is how to analyze the different data sources to build a robust learner profile and provide appropriate levels of feedback based on such profiles.

Each TRE is created with specific instructional goals and assumptions about learning. With increased access to mobile technology informal learning opportunities occur regularly. We know that mobile devices serve as just-in-time knowledge acquisition devices that are used to answer specific questions when needed. Researchers are beginning to explore how mobile devices can serve as augmented reality applications to help individuals construct new knowledge. We explore an example below of how learners can experience the past by playing with augmented reality applications on mobile devices.

**A Walk through Time: History at your Fingertips through Augmented Reality**

Historical events by definition refer to events that occurred in the past and it is difficult to recreate a past experience. One way to make history come to life is to situate learners in contexts that bring meaning to past events. As a case example, we describe a collection of augmented reality applications that are designed to help people learn by interacting with historical artifacts. The War of 1812 suite of iHistoryTour applications, designed by Kee (Kee & Darbyson, 2011), is designed to help individuals experience history as they take augmented walking tours across Niagara-on-the-Lake and Queenston. The suite includes *Niagara 1812: Return of the Fenian Shadow*, and *Queenston 1812: The Bomber's Plot*. Location-based augmented reality narratives appear based on the visitors' location near heritage sites. The War of 1812 applications relies on real-time GPS tracking to determine the visitors' progress throughout the tour and tailors the instructional content accordingly. The instruction includes interactive game-like puzzles and problems to solve to engage visitors in learning about the War of 1812. Quest Mode leads visitors through specific locations while helping them to investigate age-old mysteries, decode puzzles, and learn about historic people.

For example, visitors to the village of Queenston Ontario learn about the history of one of the most famous battles of the War of 1812. The augmented reality application guides visitors as they explore historical heritage sites, and presents them with location-based investigations, i.e., who bombed the Sir Isaac Brock monument in 1840. The plot unfolds around five locations, the Laura Secord homestead, the Queenston Baptist Church, the Wall remains, History Alley, and the Mackenzie Printery. Visitors can acquire factual information regarding each location as well as details surrounding the Battle of Queenston Heights and the suspects alleged to being involved in the bombing of the monument. In doing so, visitors' reason on the basis of historical sources, including pictorial evidence (i.e., a portrait of Laura Secord) as well as written documents (e.g., a declaration written by Colonel James Morreau). The application incorporates game-based features to demonstrate how historians evaluate the credibility of sources by comparing these sources and analyzing characteristics of artifacts. The plot unfolds around evidence collected at each location. Visitors use their evidence to reason about the causes of the bombing and they select the most likely suspect based on their evidence. Once they select a suspect the application tailors the feedback to illustrate an actual historian's reasoning about the causes of the event. Visitors learn about the importance of reasoning on the basis of credible sources and how to rule out potential explanations for historical events.

In collaboration with co-investigators from the LEADs partnership, researchers are applying existing methods and developing and evaluating new measures to gather convergent evidence of visitor learning and engagement in the context of both actual and simulated tours (Poitras, Kee, Lajoie, & Cataldo, 2013). Guided tours in the field can be virtually re-created in a laboratory setting through the use of 360-degree panoramic photos of the relevant locations displayed on a large touch sensitive screen. Users of the application can thus navigate to and from each location while changing the orientation of their view~~s~~. The laboratory setting provides opportunities for collecting data that captures the visitors' experiences at multiple time points throughout the tour, including sensors that capture behaviors (portable eye-tracking and behavioral coding application), affect (galvanic skin response, structured self-report questionnaire), as well as cognition and metacognition (audio-records of verbal discourse). These measures allow researchers to study how visitors allocate their attention to areas of interest in the interface with respect to specific locations featured in the tour, as well as appraise changes in enjoyment and boredom before, during, and after each tour location. The value added of an interdisciplinary approach to augmented reality applications to quote Kee, a digital humanist, is " While humanists are increasingly engaged in the development of augmented reality applications to communicate culture, rigorous testing for user engagement and learning with these applications is less common. Our research suggests that design and development by humanists should be coupled with evaluation by researchers of educational psychology [and informed by their theories of affect, learning and instruction.]"[1]

A pilot study was conducted on how participants used the MTL Urban Museum location-based augmented reality application developed by the McCord Museum. This study evaluated the benefits of utilizing the convergent methods mentioned above to study learning and affect (Harley, Poitras, Jarrell, Lajoie, Duffy, Cataldo, &

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[1] Personal communication from Kevin Kee, a LEADS member.

Kee, 2015). The application relies on GPS-based location markers to deliver historical photographs of the appearance and history of buildings across the campus. The aim of the study was to evaluate the ability of visitors to contextualize the past by comparing the past and present locations to highlight noticeable differences in the appearances of buildings and monuments as well as the modes of transportation. Researchers transcribed and coded the verbal transcripts to characterize the discursive strategies that were utilized by the tour guide to prompt visitors in articulating these differences. The results of the analysis of the dialogue between the visitor and guide suggest that the visitors outlined differences in building appearances, transportation modes, and the Roddick Gates itself. The involvement of the guide led to an improvement in visitors’ ability to identify differences between the past and present, resulting in 3.08 features identified with the guide compared to 1.77 without assistance. The data obtained from the eye-tracking equipment confirmed that visitors carefully attended to the material, shifting their gaze from the application to the virtual environment on an average of 48 occasions. The self-reported levels of enjoyment towards the tour, the guide, and the learning activity were consistently high before and after visiting this location, while the levels of boredom were found to be low. Using convergent methods to document learning and enjoyment in augmented reality applications can help identify what is learned, where feedback is needed, and whether participants enjoy the experience.

The motivational affordances of game-based learning have been investigated in the context of Crystal Island, a project led by James Lester and his team at the University of North Carolina. Learners engage in a realistic investigation of a mysterious disease that is spreading through an island, thereby learning about scientific concepts while performing inquiries into the problem.

**Being a Scientist: Crystal Island**

Crystal Island immerses students in a virtual world where they are acting as scientists. This game-based learning environment is designed to support learning of microbiology and scientific literacy through complex narratives (Rowe, Shores, Mott, & Lester, 2011). Learners are given meaningful tasks where they play the protagonist and investigate the identity and source of an infectious disease that is spreading throughout the island. The game allows learners to explore the island while gathering evidence about relevant diseases, forming and testing hypotheses, and recording their findings. The learners interact with members of the scientific team, test potential sources of the disease in a laboratory, and present their findings, diagnosis, and treatment plan. The scientific problem solving skills pertain to building a scientific argument about what plague has infested the island based on the scientific evidence that is collected. Crystal Island serves as both a learning and research platform, enabling the collection of user interaction data that allows for investigating automated forms of tutorial dialogue planning (Lee, Rowe, Mott, & Lester, 2014), learning goal recognition (Ha et al., 2011), and affect recognition (Sabourin, Mott, & Lester, 2013). According to Lester[2] conducting research on learning in TREs is an inherently interdisciplinary enterprise. The diversity of perspectives provided by educational psychologists, curriculum specialists, and computer scientist is essential for effectively investigating next-generation learning because we must understand 1) the

[2] Personal communication with James Lester, computer scientist and LEADS member.

principles of learning, 2) the pedagogies that support it, and 3) the design of adaptive learning technologies that are informed by these principles and pedagogies." Calvo[3] states "even the most human-centered computer researcher will bring perspectives to the problem that are very different to those of a psychologist or educator. Each one has a set of tools and research method that is unique to her discipline."

The act of learning in real-world contexts, such as learning to diagnose patient cases, has been explored use a TRE called BioWorld, designed by Susanne Lajoie and her team at McGill University. We describe this adaptive technology below.

**Learning through Deliberate Practice of Diagnostic Reasoning: BioWorld**

Learning in the medical professions is often restricted by opportunistic cases that a medical student may encounter, and the time limitations that restrict students' ability to see a patient case to its conclusion. BioWorld (Lajoie, 2009) was created to provide medical students with a learning environment to practice their diagnostic reasoning skills with virtual patients, by providing learners with a simulated environment to collect patient symptoms, run diagnostic tests, formulate and change diagnoses, and search for information in on-line libraries. Medical students are tutored and supported in this TRE by expert feedback that helps them in their diagnostic reasoning. However, diagnostic reasoning is an ill-structured problem-solving task. The challenge in modelling learning in the context of solving ill-structured problems is that there are multiple paths towards attaining the correct solution (Lajoie, 2003, 2009). These paths should be documented to represent common misconceptions or impasses in moving along the trajectory towards

[3] Personal communication with Rafael Calvo, software engineer and LEADS member.

competency. In the medical domain, there may be expert consensus on the diagnosis but they reach their conclusions taking different routes. However, these same experts justify plausible hypotheses on the basis of common evidence items, including patient symptoms and lab test information (Gauthier & Lajoie, 2014). BioWorld supports the ill-structured nature of diagnostic reasoning by using a novice-expert overlay system that models both reasoning processes, diagnostic outcomes and accuracy, and compares novice solution paths to those of the experts to individualize feedback. BioWorld traces learner interactions and highlights areas of similarities and differences with the expert solution path, allowing novices to self-reflect on their own approach to resolving the problem.

Lajoie and colleagues have explored the relationship between medical student diagnostic reasoning proficiency in BioWorld as it pertains to use of expert feedback, SRL, usage of on-line library tools, and accuracy of written case summaries. Proficiency was related to better use of feedback (Lajoie et al., 2013a), more SRL behavior, and greater use of online-library tools to supplement knowledge (Lajoie et al., 2013b; Poitras, Jarrell, Doleck, & Lajoie, 2014). The novice-expert overlay models are also useful when capturing linguistic features from written case summaries to determine differences in reasoning that can help determine where feedback content may need to be tailored (Poitras, Doleck, & Lajoie, 2014). The relationship between motivational and affective constructs while learning with BioWorld have been explored in terms of the impact of goal-orientations and affective reactions towards attention given to feedback (Lajoie, Naismith, Poitras, Hong, Panesso-Cruz, Ranelluci, & Wiseman, 2013; Naismith, 2013). Student attention to feedback in BioWorld is mediated by a number of factors including learning performance, achievement goal orientation, feedback emotions, and characteristics of how the feedback is displayed (Naismith, 2013; Naismith & Lajoie, 2014). Understanding the relative contribution of each of these factors is important for the effective design and implementation of computer-based feedback to support diagnostic reasoning.

Lajoie comments that interdisciplinary teams can expand the depth of documentation of learning trajectories. As multiple forms of learner data are collected psychometricians may look at convergent data to build theoretical models of learner profiles that can be used to predict performance. Latent class analysis of variables has the potential to discover individual-based dynamics and identify distinct learning patterns attributable to specific TRE components that ultimately can contribute to the development of profile-based design interventions in the TRE to individualize and maximize learning (Jang, Wagner, & Xu, 2014). According to Leighton,[4] "interdisciplinary approaches to assessment design ensure that all relevant factors – human, environmental, and social - are considered in the process of collecting the most accurate data about how individuals learn. In addition, such approaches force us to continually challenge and diversify our existing practices for the purpose of designing the most innovative assessments possible."

We examine the role of feedback in TRES for promoting self-regulated learning about anatomical systems. MetaTutor, developed by Roger Azevedo and his colleagues, is described below.

[4] Jacqueline Leighton, a LEADS member and educational psychologist who specializes is assessment.

**Scaffolding Science Comprehension by helping Learners Know what they Know: MetaTutor**

Some TREs are open-ended where students can explore any and all avenues that interest them in the context of their learning. Not all learners perform well in open-ended computer based environments since they cannot determine where to direct their cognitive resources. Research has shown that learners often fail to engage in regulatory processes, which can lead to decreases in learning and performance (Azevedo & Feyzi-Behnagh, 2010). MetaTutor was designed to assist learners in developing their self-regulatory skills in the context of learning about complex biological systems in an adaptive multi-agent hypermedia-learning environment (Azevedo et al., 2008; Azevedo et al., 2014; Azevedo, Johnson, Chauncey, & Burkett, 2010). Azevedo and colleagues based their design of MetaTutor on empirical research that examined the effectiveness of specific self-regulatory processes while interacting with human tutors; as a result, the design of MetaTutor includes pedagogical agents that emulate human tutor interactions in an adaptive manner (see Azevedo, 2008;). MetaTutor allows learners to interact with several pedagogical agents while learning about science. In doing so, learners receive scaffolding in terms of setting goals for their learning, monitoring their progress, using learning strategies to better achieve these goals, and handling task difficulties and demands. These self-regulatory processes involve cognitive, metacognitive, motivational, and affective activities that unfold during learning. Learners engage in these regulatory processes to transform information about biological systems from multiple types of representation.

Before learning with MetaTutor, learners have the benefit of instructional videos where self-regulatory skills are modeled, a discrimination task where learners recognize appropriate and inappropriate uses of these strategies, as well as a detection task where the learners identify the onset of a self-regulatory strategy. During the actual learning task, the learners have the benefit of pedagogical agents, menus to select and organize the subject matter and learning subgoals, as well as various representations of the science content. The pedagogical agents provide feedback within the tutorial dialogue to support learners to select appropriate goals, judge their degree of understanding in an accurate manner, and use effective learning strategies. The learners utilize a palette to engage in specific metacognitive monitoring and control activities.

MetaTutor records user interactions for the purposes of providing adaptive feedback towards the deployment of self-regulatory processes. On the basis of detecting patterns in learner behaviors, the pedagogical agents may prompt learners to make a metacognitive monitoring judgment. Once the learners are prompted to monitor their learning, a brief quiz is administered to tailor the content of the feedback to the individual needs of different learners. This computational model is evaluated and iteratively revised through the collection of converging data gained from multiple sources, including self-report measures of self-regulatory processes as well as online measures such as concurrent think-aloud protocols, tutorial dialogues, physiological signals, eye-tracking data, and facial data of emotional reactions. These types of data complement the findings obtained from the log-file record of user interactions, including note-taking behaviors, drawing, selections, as well as performance on embedded quizzes. These sources of data enable researchers to characterize the deployment of self-regulatory processes by examining the temporal aspects of specific processes, the navigational paths across hypermedia content, and fixation patterns across interface elements (Azevedo, et al., 2010; Azevedo & Witherspoon, 2009), patterns of learner interactions (Bouchet, Azevedo, Kinnebrew, & Biswas, 2012), and the onset of emotional reactions (Harley, Bouchet, Hussain, Azevedo, & Calvo, 2015).

Empirical research using Metatutor has demonstrated how and when specific self-regulatory agents assist learners in their use of such skills to learn about the circulatory system in a hypermedia environment. More specifically they have identified specific precursors to the use of self-regulatory skills in the context of learning in this advanced technology.

## Conclusion

The metaphor of using technology as a tool to augment our thinking has undergone significant change during the last decade, so much so that technology-rich learning environments rely on them to target not only cognitive, but also metacognitive, affective, and social processes. As such, we have argued that the metaphor of cognitive tools be broadened in terms of the breadth and depth of constructs that are targeted through the use technology. These tools are embedded in technology-rich learning environments with the aim of enhancing learning and performance across a broad variety of tasks and disciplines, to the benefit of a range of learners with varying characteristics, backgrounds, and needs. Given these rapid developments in learning theories, the challenge is to design affective and metacognitive tools that are capable of accurate and reliable assessment of these latent and complex processes.

Pellegrino, Chudowsky & Glaser (1991) claim that effective teaching relies on a triad of factors, where the curriculum topic, instructional approach, and assessment method complement each other in terms of achieving a well-defined objective. This paper has reviewed several examples of technology-rich learning environments studied in the LEADS partnership that align curriculum, instruction, and assessment, enabling the underlying system to adapt itself to the varying and important events that characterize learning processes and outcomes before, during, and after task performance (Lajoie, 2014). These affordances of technology-rich learning environments can take many forms, as learners engage in optimal learning through one-on-one tutoring with pedagogical agents, models of proficiency that are externally represented through the system interface, repeated opportunities for practice and feedback, as well as increased autonomy and self-directedness in task performance.

A direction that needs to be expanded in the area of adaptive technologies is one that considers the social emotional perspectives of learning. As theories of learning have adjusted to consider the social influences on cognition, many self-regulation researchers have broadened their scope to examine co-regulation and socially shared regulation of knowledge (Hadwin & Oshige, 2011; Järvelä & Hadwin, 2013; Volet, Vauras, Khosa, & Iiskala, 2013). These researchers describe how group members influence the growth of self-regulation (Hadwin & Oshige, 2011; Järvelä & Hadwin, 2013). As these theories grow so do the designs of advanced technologies to encourage co-regulation and to assess the influence of social-emotional processes on learning using technologies (Lajoie et al. 2014). Methodological innovations must be created to represent and analyze the multiple voices that contribute to co-regulation and learning.

Advances in learning analytics and data mining techniques are assisting researchers to mine large data sets to find meaningful patterns in group-discourse that lead to learning. We see this as an emerging field. TREs are now capable of accumulating large volumes of data on learners and computational challenges have arisen that call for further research in the refinement and development of learning analytics and reporting tools (Cooper & Sahami, 2013; Buckingham Shum, Hawksey, Baker, Jeffery, Behrens, & Pea, 2013; Kay et al., 2013; Siemens & Long, 2011; Williams, Koedinger, Renkl, & Stamper, 2013). There has been rapid growth in the development of data mining and analytics in the field of education during the last decade (Baker & Yacef, 2009; Romero & Ventura, 2010). Notable initiatives within this field include the Pittsburgh Science of Learning Center DataShop, the largest open repository of data on learner interactions with intelligent systems (see Koedinger, Baker, Cunningham, Skogsholm, Leber, & Stamper, 2010), as well as the creation of standards for logging educational data (i.e., Aggregator for Game Environments; Generalized Intelligent Framework for Tutoring; see Owen & Halverson, 2013; Sottilare, Goldberg, Brawner, & Holden, 2012; Sottilare, Hu, & Graesser). Using log-file databases of user interactions, researchers have utilized data mining techniques, including clustering, classification, and sequential pattern mining algorithms, in order to accomplish several tasks, such as predicting learner performance, generating recommendations, detecting undesirable behaviors, and grouping learners into usable profiles (see Baker & Yacef, 2009: Romero & Ventura, 2010). The large-scale databases that are generated in the context of such platforms provide an important opportunity for researchers to exploit educational data in order to develop automated methods of assessment. Furthermore, as the learning theories that inform design metaphors continues to expand, there is a need for increased research into multimodal data mining and learning analytics in order to target the cognitive, metacognitive, affective, and social processes that mediates learning.

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