Deep Learning and Emotion in Serious Games

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Theories of Learning and Emotion Underlying Serious Games

Serious games are designed with the explicit goal of helping students learn about important subject matter content, problem solving strategies, and cognitive or social skills. Instead of learning about biology by reading a textbook, listening to a lecture, or interacting with a conventional computer-based training system, the learner plays a game that successfully integrates the game with curriculum. If we could manage to design serious games, the impact would be revolutionary because the learning of difficult content would end up being an enjoyable, engaging experience for the learner. Intellectual hard work would be transformed into play.

Unfortunately, at this point in the learning sciences, very few serious games have been developed that would impress experts in education. This has led some researchers and game developers to speculate that game design may be inherently incompatible with pedagogy (see Prensky, 2000). The optimistic view is that there needs to be careful analysis of how the features of games are systematically aligned with the features of pedagogy and curriculum (Gee, 2004; Gredler, 1996; O'Neil, Wainess, & Baker, 2005; Rieber, 1996; Shaffer, 2007; Van Eck, 2007). For example, Van Eck (2007) analyzed how Gagne's principles of instructional design (Gagne, Wager, Golas, & Keller, 2004) are mapped onto particular features of games. O'Neil et al.(2005) presented a similar mapping of game features to Kirpatrick's (1994) four levels of evaluating training (student reaction, learning, behavioral transfer, and systemic results) and to Baker and Mayer's (1999) model of learning that has five major families of cognitive demands (content understanding, problem solving, self-regulation, communication, and collaborative teamwork).

The design, development, and testing of serious games are at an early stage of evolution so there is not a large empirical literature on how well they facilitate learner's reactions and learning. Ideally, the learner's reaction to serious games would increase enjoyment, interest in the topic, and what Csikszentmihaly (1960) has called the *flow* experience. Flow is experienced when the learner has such intense concentration that time and fatigue disappear. Such engagement in the game would be expected to facilitate learning by virtue of time on task, motivation, and self-regulated activities, as long as the focus is on the instructional curriculum rather than exogenous game components. Available reviews and meta-analyses have not provided overwhelming support that serious games enhance learning of content, strategies, or skills (Fletcher & Tobias, 2007; O'Neil et al., 2005; Randel, Morris, Wetzle, & Whitehead, 1992). O'Neil et al. (2005) reported that there are less than 20 published journal articles that have the scientific rigor for a meaningful quantitative assessment of learning gains compared to control conditions. Nevertheless, these reviews uniformly recommend that adequate assessments require a behavioral, cognitive and social task analysis between the game features and the desired learning objectives. There are documented success cases that show the promise of serious games, such as Gopher, Weil, and Bareket's (1994) transfer of the *Space Fortress* game to piloting real aircraft, Green and Bavelier's (2003) transfer of action digital games to visual selective attention, and Moreno and Mayer's (2005) use of experimenter-constructed games to train explanations of scientific mechanisms.

Theoretical analyses of games, game taxonomies, and game features have frequently been proposed by game designers (Gredler, 1996, Salen & Zimmerman, 2004) and researchers (Gee, 2004; Malone & Lepper, 1987; O'Neil et al., 2005; Rieber, 2006;

Shaffer, 2007; van Eck, 2007; Vorderer, Bryant, Pieper, & Weber, 2006). A consensus has not yet emerged on the necessary, sufficient, and primary features of games, but there is reasonable agreement on the basic categories of games that can classify the wide diversity of games in the market (Academy of Interactive Arts and Sciences; Gamespot.com; Green & McNeese, 2007; Smith, 2006). Some example genres of games in these taxonomies are first-person shooter (e.g., *Halo 3*), action/adventure (*Myst*), strategy (chess), puzzle (*Tetris*), trivia (*Jeopardy*), simulation (*SimCity*), role playing (*Dungeons & Dragons*), and massively multiplayer online (*EverQuest*) genres.

The game genres can be aligned with specific behavioral, cognitive or social skills that are acquired and automatized as a function of increasing playing time, practice, tests, and challenges. These skills span perception-attention-motor skills, working memory management, memory for content, reasoning, planning, problem solving, and social interaction. The field needs a theoretical framework that maps the game genres and game features onto theoretical components of cognition, emotion, motivation, and social interaction (Moreno & Mayer, 2005; O'Neil et al., 2005). Deeper levels of learning would involve many different elements, including an analysis of causal mechanisms, logical explanations, creation and defense of arguments, management of limited resources, tradeoffs of processes in a complex system, and a way to resolve conflictsThese activities require reasoning and are taxing on cognitive resources (Bloom, 1956; Chi et al., 2001; VanLehn et al., 2007). More shallow levels include perceptual learning, motor skills, definitions of words, properties of objects, and memorization of facts. Aside from the depth of skills afforded by a game, there is the persistent question of their utility and relevance to the real world.

The scientific status of the game features proposed by game designers is greatly in need of computational and empirical inquiry. All games have *rules*, *actions* of the player, *uncertainty* in outcomes as the game progresses, and *feedback* on the outcomes that occur. The uncertainty creates suspense, one of the prominent entertaining features that sustain one's attention (Cheong & Young, 2006; Vorderer, Wulff, & Friedrichsen, 1996; Zillman, 1996). Many games have points, rewards, competition, winners versus losers, and different levels of privilege that are tied to prior successes, but these features are not universal to games. Aside from the computational essence of games, there is the question of what makes them successful psychologically (Loftus & Loftus, 1983; O'Neil et al., 2005; Vorderer & Bryant, 2006). At this point in the science, there are few firm answers to such questions about the essence of games and their psychological impact, but the available literature offers a number of suggestions, as illustrated below.

(1) **Interest, Challenge, and Fantasy**. When Malone and Lepper (1987) analyzed the features of successful digital games on the market, the features they identified were the arousal of interest, challenge, and fantasy. Ideally these features would be *endogenous* to educational content and skills in a serious game, rather than to the frivolous aspects of the game that are *exogenous* to content.

(2) **Play**. Games have the potential of integrating work and play (Rieber, 1996; Van Eck, 2007) by incorporating different forms of play that appeal to progress, fate, power, identity, imagination, and self. However, the integration is tricky because many players become turned off if the environment looks similar to formal education. Players do not want to read or listen to a lecture on technical content; instead this content needs to be seamlessly integrated with play.

(3) **Challenge and the Goldilocks Principle**. Games have an optimal level of challenge that is at a level of not being too hard or too easy, but just right (i.e., the *Goldilocks principle*). A good game is at the zone of proximal development (Vygotsky, 1978) or at the brink of other zones of ability, cognition, and emotion (Conati, 2002; Rieber, 1996). A game that is slightly more challenging than the learner's skill and knowledge may sustain interest by providing accomplishment while maintaining effort. Success breeds self-efficacy, which is highly correlated with interest in games and learning environments in general (Lepper & Woolverton, 2002).

(4) **Feedback**. Feedback on performance in the form of immediate corrections, explanations, cumulative points, mastery of specific content, and skillometers can facilitate engagement, effort, and self-efficacy in many instructional technologies (Anderson, Corbett, Koedinger, & Pelletier, 1995; Foltz, Gilliam, & Kendall, 2000; Jackson & Graesser, 2007; Shute, 2006). However, game designers emphasize that the feedback should not appear too much like taking a test in a formal educational environment.

(5) **Instructional Support**. Instructional support can facilitate learning from games (Moreno & Mayer, 2005; Shaffer, 2007; Swaak & de Jong, 2001; Rieber, 2005), including guidance, explanations on feedback, and prompted reflection. Shaffer (2007) has encouraged a tutor or mentor for complex games to assist the player in getting started, articulating strategies, and modeling important interactions with the game.

(6) **Narrative**. Many games are embedded in a story narrative with characters/players, a setting, a conflict/competition, action episodes of players, and outcomes. Narrative has a special status in cognitive system (Bruner, 1986; Graesser,

Singer, & Trabasso, 1994; Read & Miller, 1996; Schank & Abelson, 1995), being comprehended quickly and remembered well compared with other genres (Graesser & Ottati, 1995). Unlike text or film, narrative in games has a distinctive status because the story plans are co-constructed interactively between the player and game system (with or without other players) and because a player can experience hundreds of game threads rather than a single episodic sequence (Gee, 2004; Van Eck, 2007; Vorderer, 2000; Young, 2006).

(7) **Hypothetical Worlds and Eventualities**. Games allow the learner to explore many hypothetical worlds and eventualities rather than being constrained to a single situation model. O'Neil et al. (2005) have contrasted simulation and games with respect to the integrity of the simulated trajectories and outcomes, with the former having some integrity in the causal mechanisms but games potentially following arbitrary rules or algorithms. However, serious games would be expected to have an accurate simulation that instantiates the targeted causal mechanism.

(8) **Entertainment and Enjoyment**. Vorderer, Klimmt, and Ritterfeld (2004) pointed out that enjoyment is the core of the entertainment process, including the experience of games. The entertainment value of a game can be predicted by (a) sensory pleasure, which comes with photorealism and immersion, (2) the emotions of suspense, thrill, and relief, which are influenced by one's caring for characters and a strong narrative, and (3) the motivational factors of achievement, control, and self-efficacy, which should be influenced by the degree of interactivity.

(9) **Types of Interest**. Interest signifies that underlying needs or desires of learners are energized (Alexander, Murphy, Woods, Duhon, & Parker, 1997). Motivation

researchers contrast *individual interest* that springs the desire to develop competence and personal investment versus *situational interest* that reflects a transitory, short-lived interest within an immediate situation or context (Alexander et al., 1997; Hidi & Harackiewicz, 2000).

From our perspective, the primary challenge in designing serious games is to find ways to facilitate deep learning rather than shallow learning. There are several games that help learners acquire shallow knowledge and skills, i.e., perceptual learning, motor skills, definitions of words, properties of objects, and memorization of facts. It remains an open question how efficient the games are from the standpoint of the amount learned per unit time compared to alternative learning environments. In contrast, there a very few games that promote the acquisition of deep knowledge, strategies and skills, such as: understanding causal mechanisms, generating explanations and well-formed arguments, critical reasoning, precisely monitoring of tradeoffs between variables, managing limited resources, resolving conflicts in complex systems, satisfying multiple constraints, and applying old solutions to new problems in the real world. Yet deep learning is essential in modern societies where there is a serious shortage of expertise in science, technology, engineering, and mathematics (STEM).

Intelligent Tutoring Systems (ITSs) are the best example of computer environments that promote deep learning so it would be worthwhile to explore the advantages of incorporating the above features of games into existing ITSs. Serious games presumably engage students more than traditional tutoring environments. However, we do not know which components of games are most critical for capitalizing on the seductive aspects of games for deep learning. It is an open question how to develop *serious deep games*, as we will explore throughout this chapter.

Is Deep Learning Compatible with Serious Games?

Serious games presumably need to be buttressed by psychological theories of behavior, cognition, emotion, and social psychology. Links between games and psychology have been identified in a number of books, papers, and research efforts (Loftus & Loftus, 1983; O'Neil et al., 2005; Vorderer & Bryant, 2006), but the empirical evidence is modest at best. Given the growing popularity of games in the United States and throughout the world, one might have expected a generation of psychologists to be forming new societies and journals as they investigate the psychology of games. But that has not happened. Somehow psychology has ended up being detached from the $10 billion game in the United States, where half of the citizens play games (Entertainment Software Association, 2004). Mainstream game industries are not currently hiring psychologists in droves, but perhaps that opportunity will be realized in the future.

Why is psychology functionally out of the loop of the commercial game market? The argument we want to advance in this chapter is that there are complex reasons for the detachment, but hopefully these will not be insurmountable in the future. The crux of our argument is that the constraints of complex learning, emotions, and game architecture are often very different from each other and that it will take some systematic, detailed science and engineering to satisfy the constraints of all three systems. Indeed, there are sometimes tradeoffs or incompatibilities between the three systems that present challenges and nontrivial obstacles. Solutions will require some tedious wiring between the components of very different systems.

We have one example that very much gets at the heart of the issue. A doctoral student, Tanner Jackson, recently completed his dissertation on the role of feedback in a learning environment that we developed in the interdisciplinary Institute for Intelligent Systems at the University of Memphis (Jackson & Graesser, 2007). The learning environment was AutoTutor, an intelligent tutoring system that helps people learn by holding a conversation in natural language. Students work on difficult questions on the topic of computer technology or physics by having a turn-by-turn dialogue with AutoTutor (Graesser, Chipman, Haynes, & Olney, 2005; Graesser, Lu et al., 2004; VanLehn, Graesser, et al., 2007). The details of the system are irrelevant, from the present standpoint, other than to say that the system was designed to promote deep explanatory reasoning about mechanisms in technology and science, as opposed to shallow knowledge (e.g., definitions of terms, properties of entities, recognition of explicit ideas). College students learned with different versions of AutoTutor and were given pre-tests, post-tests, and rating scales of how much they liked the learning experience. The pre-tests and post-tests were multiple-choice questions and open-ended essay questions that tapped deep levels of comprehension. One of the interesting results of the dissertation was the negative relationship between learning and the students' self-report ratings on how much they liked the learning environments. As more deep learning occurred, the less the students liked the learning environment. The results were compatible with the adage "No pain, no gain." There was clearly a tradeoff between complex learning and positive emotional valences: the deeper the learning, the more negative the emotional response.

It is conceivable that a serious game architecture could mitigate the negative correlation between liking and deep learning. We could add on another layer to AutoTutor in which there is an increase in points, choice options, fantasy worlds, or empowering tools when the player exhibits deeper learning. Will there still be a tradeoff between deep learning and affect with these components of reinforcement? There is no empirical research that has investigated the complex interactions among complex learning, emotions, and game architecture.

Another practical example of the difficulties of these interactions is in our recent work on learning communities for serious games. In the fall of 2006, the four authors of this paper organized a learning community for college freshmen on the design of serious games. Each of the 26 students in the learning community took a common set of four courses on game design, psychology, problem solving with computers, and English composition. The students were divided into groups and each group spent the semester designing a serious game on psychology content by integrating what they learned in the four courses. There were 6 groups and their games were designed, revised, and refined over the course of the semester as the students integrated these various bodies of knowledge. The students read books on game theory and design (Gee, 2004; Salen & Zimmerman, 2005) while they designed the games in the design teams. One of the courses helped them learn how to program the computer with software for novices to design games and multimedia environments (Sherrell et al., in press). However, the games they designed ended up being board games because there was not enough time in a single semester for students to implement the games on computer.

The learning community was very successful in many respects. The attendance of the students was extremely high in the courses and the morale of the students was unusually positive by all objective indicators. They also acquired the typical amount of traditional content in each of the academic courses in psychology, computer science, and composition. However, the games did not integrate a sophisticated level of knowledge about psychology. The games had analogies to traditional games like *Trivial Pursuit*, *Monopoly* (e.g., a game called *Psychopoly*), and *Pictionary*. The psychology content referred to trivial facts and shallow knowledge, such as Freud being the father of clinical psychology, the composition of neurons, and the distinction between short-term memory and long-term memory. One group attempted to integrate knowledge about the behaviors exhibited in psychological disorders through a game like charades, but this game only required exhibiting shallow knowledge in the diagnosis of such disorders. Deep knowledge about psychological mechanisms was conspicuously absent.

It is perhaps not surprising that the students' games were pitched at shallow levels because the students had only introductory knowledge of psychology, textbooks and other reading materials in introductory psychology tend to be shallow, and the students had to design the game before they were finished with the course. In fact, the learning community we taught in 2007 was modified so the students learned more about psychology and more about game designs to promote deeper learning before the groups started designing their games. Nevertheless, it just might be the case that the constraints of games make it extremely difficult to integrate deep content, strategies, and skills. The complex mechanisms of psychology may have very few alignments or may even be incompatible with the essential hooks of engaging interesting games. This may explain why there are very commercial games that would be considered serious games for promoting deep learning of science, technology, engineering, and mathematics. One of the challenging research questions for the future is how to design serious deep games.

Relationships between Deep Learning and Emotions

Connections between emotions and learning are receiving more attention in the fields of psychology (Dweck, 2002; Lepper & Henderlong, 2000), education (Meyer & Turner, 2006), neuroscience (Damasio, 2003), and computer science (Kort, Reilly, & Picard, 2001). A satisfactory understanding of such emotion-learning connections is necessary to design engaging learning environments that motivate students to learn. Consequently, factors that promote emotions and motivation have been surfacing in advanced learning environments such as intelligent tutoring systems (De Vicente & Pain, 2002; Graesser et al., 2006; Litman & Forbes-Riley, 2004) and serious games (Conati, 2002; Gee, 2004).

What mechanisms might theoretically relate emotions with learning? Psychologists have developed theories that link cognition and emotions very generally (Barrett, 2006; Mandler, 1984; Ortony, Clore, & Collins, 1988; Russell, 2003; Stein & Hernandez, in press), but most of these do not concentrate on the process of learning per se. Ekman's classical work on the detection of emotions from facial expressions (Ekman, 2003) examined primarily the six basic emotions of sadness, happiness, anger, fear, disgust, surprise. However, these emotions have minimal relevance to complex learning (Graesser et al., 2006; Kort et al., 2001). Pervasive affective states during complex learning in a 1-hour tutorial session include confusion, boredom, flow/engagement, curiosity/interest, delight/eureka, and frustration from being stuck (Burleson & Picard, 2004; Craig et al., 2004; Csikszentmihalyi, 1990; Graesser et al., 2006; Kort et al., 2001).

There are a number of theoretical frameworks that predict systematic relationships between emotions and learning of complex material. Most of these have direct relevance to the design of serious games. Meyer and Turner (2006) identified three major theories that they called academic risk taking, flow theory, and goal theory. The *academic risk theory* contrasts the adventuresome learners versus cautious learners. Adventuresome learners are typically, but not always, those with high ability. They want to be challenged with difficult tasks, take risks of failure, and manage negative emotions when they occur. Cautious learners prefer easier tasks, take fewer risks, and minimize learning situations in which they fail and experience negative emotions. These differences in learners could be accommodated in serious games if the system could somehow infer the learner's emotional profile and proclivities to taking academic risks, and then present challenges within an optimal zone of risk.

According to *flow theory*, the learner is in a state of flow (Csikszentmihaly, 1990), when the learner is so deeply engaged in learning the material that time and fatigue disappear. A model proposed by Metcalfe and Kornell (2005) predicts that the flow experience is optimized when the learning *rate* is high and the learner eventually achieves a high level of mastery. Thus, engagement is lower when the learner starts out performing well, when minimal learning occurs, and/or when their achievements never reach an acceptable level. Serious games would benefit from a mechanism that optimizes the pleasurable flow experience by dynamically adjusting parameters of learning rate, game challenges, feedback on achievements, and so on.

Goal theory emphasizes the role of goals in predicting emotions. Outcomes of behaviors that achieve goals are reinforcing and result in positive emotions whereas outcomes that jeopardize goal accomplishment result in negative emotions (Dweck, 2002; Stein & Hernandez, in press). Obstacles to goals are particularly diagnostic of both learning and emotions. The affective state of confusion correlates positively with learning gains presumably because it is accompanied by deep thinking (Craig et al., 2004; Guhe et al., 2004). Confusion is diagnostic of *cognitive disequilibrium*, a state that occurs when learners face obstacles to goals, contradictions, incongruities, anomalies, uncertainty, and salient contrasts (Festinger, 1957; Graesser, Lu, Olde, Pye-Cooper, & Whitten, 2005; Graesser & Olde, 2003; Piaget, 1952). Cognitive equilibrium is restored after thought, reflection, problem solving and other effortful deliberations. Serious games could be designed to place the players in cognitive disequilibrium and have them conquer the impasses, thereby boosting self-efficacy. This would occur in multiple cycles throughout the game. Parameters such cycle phase duration and degree of challenge would need to be tailored to the emotional and cognitive profile of the learner.

As mentioned earlier, human tutoring and intelligent tutoring systems (ITSs) are regarded as the best learning environments to promote deep learning of content, strategies, and skills (Aleven & Koedinger, 2002; Chi et al., 2001; Cohen et al., 1982; Dodds & Fletcher, 2004; Van Lehn et al., 2007). Researchers have considered the possibility that a tutoring environment that is sensitive to a learner’s emotions would enhance learning from tutors even further (D’Mello, Picard, & Graesser, 2007; Graesser, Jackson, & McDaniel, 2007; Lepper & Woolverton, 2002; Litman & Forbes-Riley, 2004). If the learner is frustrated, for example, the tutor would generate hints to advance the learner in constructing knowledge or would make supportive empathetic comments to enhance motivation. If the learner is bored, the tutor would need to present more engaging or challenging problems for the learner to work on. If the learner is engaged in the flow state, then the tutor would presumably lay low and let the learner maintain control over the learning experience. If the learner is confused, then the tutor might attempt to keep the learner in the confused state for a period of time to encourage thinking, but would eventually need to step in to prevent the learner from getting dispirited. Since a state of confusion is positively correlated with learning events (Craig et al., 2004), it will be important to have the tutor's actions manage the learner's confusion productively. Some learners tend to give up when they are confused because they attribute their confusion to having the trait of low ability (Dweck, 2002; Turner & Meyers, 2006); these learners need to be encouraged and also informed that working on the problem will be fruitful and that confusion is a sign of thoughtful progress. Other learners get motivated when they are confused because it is a signal that they are being challenged and they have confidence in their ability to conquer the challenge. These relations between emotions and complex learning are of course quite relevant to the design of serious games that promote deep learning.

We are currently in the process of developing a version of AutoTutor that is sensitive to both the cognitive and affective states of the learner (D'Mello et al., 2007; Graesser, Jackson, & McDaniel, 2007). AutoTutor is an intelligent tutoring system that helps students learn by holding a conversation in natural language (Graesser et al., 2005). Assessments of AutoTutor on learning gains have shown effect sizes of approximately 0.8 standard deviation units in the areas of computer literacy (Graesser et al., 2004) and

Newtonian physics (VanLehn, Graesser et al., 2007). AutoTutor presents challenging questions to the learner that require about a paragraph of information to answer correctly. The typical response from the learner on any one conversational turn is very short, usually only one word to two sentences in length. Therefore, AutoTutor uses a series of pumps (“What else?”, “uh huh”) to request additional information and prompts for the learner to express specific words. AutoTutor also uses hints, assertions, and feedback to elicit responses from the learner that lead to a complete answer the question.

An automated emotion classifier is needed to make AutoTutor, other learning environments, and serious games responsive to learner emotions. We have previously reported some empirical studies that collect the dialogue history, facial action units, position of their body, and other sensory channels while they learn with AutoTutor (D’Mello et al., 2007). There are systematic relations between these sensing channels and particular emotions. For example, learner emotions are predicted by (a) the occurrence of AutoTutor’s feedback, (b) relations to the type of feedback (positive, neutral, negative), (c) the directness of AutoTutor’s dialogue moves (hints are less direct than assertions), and (d) the quality of learner’s contributions. Regarding the nonverbal channels, emotions are correlated with particular facial expressions (Ekman, 2003; Kaliouby & Robinson, 2005), posture, and face-posture combinations (D’Mello et al., 2007). When speech is recorded, affective states may be induced from a combination of lexical, acoustical, and prosodic features (Litman & Forbus-Riley, 2004). The features from the various modalities can be detected in real time automatically on computers, so we are currently integrating these technologies with AutoTutor.

These emotion-sensing technologies could be used to track the relations between learning and emotions in serious games. The above sensing channels are non-intrusive and indirect in the sense that the learners are not hooked up to sensors and equipment that the learner believes is recording their physiological arousal or brain states. Intrusive technologies directly measure the arousal of the autonomic systems, as in the case of GSR and heart rate, or brain mechanisms, as in fMRI (Mathiak & Weber, 2006), evoked potentials, or transcranial stimulation. One direction for future research is to track both intrusive and non-intrusive sensing channels while learners interact with games. Which of these channels are most diagnostic of different emotions during the experience of playing a serious game? How are the measures from these different channels inter-correlated within and across emotions?

Prospects of Developing Serious Deep Games

Psychology has already had a theoretical impact on game design by virtue of operant and classical conditioning. We see operant conditioning at work whenever we go into a casino and observe hundreds of people pulling handles and pushing buttons under a variable interval or a variable ratio schedule of reinforcement. We see classical conditioning at work when we see marketers of games casting their products in sex and violence. These are obvious examples of applying psychology principles to the design of games *per se*, but not necessarily serious educational games that attempt to facilitate deep learning. Operant and classical conditioning do not go the distance in optimizing and explaining serious games that promote deep learning.

This section explores the prospects of building serious deep games. The games we have in mind are serious in the sense that the users end up learning content that is aligned with curricula in school systems. The games are deep in the sense that the content and skills tap deep reasoning, critical thinking, complex systems, causal chains and networks, and other difficult material that is part of Science, Technology, Engineering, and Mathematics (STEM). As discussed earlier, there are few examples of serious deep games and precious little empirical research on their effectiveness in promoting learning.

Costs of Modern Learning Environments

There has been a revolution in technology-based training since the advent of the computer. Fifty years ago there were none of the following genres of learning environment: (1) computer-based training, (2) multimedia, (3) interactive simulation, (4) hypertext and hypermedia, (5) intelligent tutoring systems, (6) inquiry-based information retrieval, (7) animated pedagogical agents, (8) virtual environments with agents, (9) serious games, and (10) computer supported collaborative learning. Most of these (3-10) were not available 20 years ago and most are not mainstream technologies in schools today. However, the Web has either exemplars or mature technologies for all ten of these technologies, so they are potentially available to all Web users. These learning environments implement pedagogical mechanisms such as mastery learning with presentation-test-feedback-branching, building on prerequisites, practice with problems and examples, multimedia learning, modeling-scaffolding fading, reciprocal training, problem-based learning, inquiry learning, and collaborative knowledge construction (Graesser, Chipman, & King, 2007). Nearly all of these mechanisms emphasize that the learner actively constructs knowledge and builds skills, as opposed to merely being exposed to information delivered by the learning environment.

The learning environments vary significantly in development costs, with games being at the high end of the continuum. We recently estimated the ball-park costs of some of the alternative learning environments (Graesser, Chipman, & King, 2007). Approximate costs for an hour training session with conventional computer-based training would be $10,000, for a 10-hour course with conventional computer-based training and rudimentary multimedia would be $100,000, for an information-rich hypertext-hypermedia system would be $1,000,000, for a sophisticated intelligent tutoring system without authoring tools would be $10,000,000, and for a serious game on the Web with thousands of users would be $100,000,000. These cost estimates are of course gross approximations, but it is important to acknowledge that a successful commercial game requires $5 to $10 million to develop.

The costs of the sophisticated ITSs and immersive virtual environments are dramatically reduced by using authoring tools or by modifying existing game engines. However, it is widely acknowledged that it is nearly impossible to use the authoring tools and game engines without knowledge of computer science (Murray, Ainsworth, & Blessing, 2003; Van Eck, 2007). It is impractical to expect an instructor or curriculum developer to use these tools and engines without a substantial amount of training in computer technologies. It would be more practical to have a research team that covers expertise in pedagogy, psychology, computer science, art, economics, and marketing. Such a research team would presumably be an expensive proposition. The academic communities have pursued this team approach (Johnson & Beal, 2005; Young, 2006; Zyda, 2006) on projects funded by the government for several million dollars, but the commercial game industry does not incorporate expertise in pedagogy and psychology.

Immersive Worlds with Animated Conversational Agents

Animated conversational agents have become increasingly popular in advanced learning environments (Atkinson, 2002; Baylor & Kim, 2005; Graesser et al., 2005; McNamara, Levinstein, & Boonthum, 2004; Reeves & Nass, 1996). The agents take on roles of mentors, tutors, peers, players in multiparty games, and avatars in the virtual worlds. They can be designed to have different cognitive abilities, expertise, personalities, physical features, and styles. The agents in some of these systems are carefully scripted and choreographed, whereas agents in other systems are dynamic and adapt to the user. The users communicate with the agents through speech, keyboard, gesture, touch panel screen, joystick, or conventional input channels. In turn, the agents express themselves with speech, facial expression, gesture, posture, and other embodied actions. When an agent reaches the sophistication of having speech recognition and natural language generation, it holds a face-to-face, mixed-initiative dialogue with the student, just as people do in everyday conversations (Cole et al., 2003; Gratch et al., 2001; Johnson & Beal, 2005). Quite clearly, these worlds create a sense presence that is akin to everyday experiences in our social and physical worlds.

The animated agents will continue to be prevalent in most game environments. The field is on the brink of designing intelligent cyber agents that are indistinguishable from avatars controlled by humans. As we discussed earlier, learning will be facilitated by a tutor or mentor who guides and scaffolds interactions with a game (Shaffer, 2007). Such tutors and mentors will be extremely important additions to serious deep games because students are prone to settle for shallow learning without such external scaffolding to encourage deep learning.

Psychological Principles and Mechanisms

This chapter has already identified some of the psychological principles and mechanisms that drive successful games. The primary challenge is to identify which of these principles and mechanisms should be aligned with particular subject matter content, skills, and categories of learners. For example, the principles/mechanisms described earlier included curiosity, interest, control, fantasy, feedback, adaptivity, narrative experience, enjoyment, cognitive challenge, and the Goldilocks Principle (i.e., the game should not be too hard and not too easy, but just right – hence the Goldilocks principle). Under what conditions should each of these principles and mechanisms be recruited by game designers who have the goal of building a serious deep game? It probably would not be prudent, for example, to have fantasy guide the design of a game to help Navy personnel operate a ship.

It may be difficult to have narrative experience aligned with deep learning of science. How would the game designer weave in a captivating story that keeps the player engaged? It is difficult enough to write a captivating story, so the difficulty is compounded by incorporating deep knowledge about the subject matter. We can learn about history, shallow knowledge, and trivia though story games, but how can we learn about complex scientific mechanisms? Perhaps we could learn about blood circulation through an interesting story about the journey of a drop of blood that gets transformed in its travel. But as soon as the constraints of the circulatory system appear, the story runs the risk of meandering and becoming boring. As soon as we get on a roll with an interesting story, the integrity of the circulatory system runs the risk of degenerating. Detailed mappings between the world of science and the world of narrative are needed but there is no guarantee that there will end up being any mapping that satisfies the mutual constraints.

SimCity is one example of a mass-market game with educational value. In *SimCity*, the player takes on the role of a mayor and city manager who is tasked with building a thriving metropolis from an empty plot of land. The player has a wide variety of controls available to accomplish this goal, ranging from specifying the zoning of parts of the city to implementing ordinances to change the behavior of its inhabitants. The game provides little immediate guidance on what actions the player should take; instead, it offers feedback over time as the simulation progresses, as well as more immediate feedback from both virtual “advisors” who can be consulted about the needs of the city and also a “news ticker” that scrolls across the scene to warn of problems that require direct, prompt action (such as natural disasters or missing infrastructure).

SimCity does not provide a drill and practice environment nor or any form of direct didactic content delivery. However, it does educate in a constructivist framework that incorporates most of the principles and mechanisms of serious games. Players “learn by doing” and trial and error as they approach both the larger problem of building a large city from nothing as well as the smaller sub-problems presented by the effects of the choices they make and the vicissitudes of city growth. The simulation provides feedback by modeling the results of the player’s decisions. A choice to bring in a casino, for example, would bring in vastly increased tax revenue from tourism, but simultaneously would have the side effects of increased crime and reduced property values. An understanding of the unwanted side effects requires the discovery of a causal network of variables, propagation of constraints, tradeoffs, and resource limitations. By manipulating the system and observing the results, players can implicitly (through reasoning) or explicitly (through experimentation) learn the rules of the city simulation that are aligned with the complex social system. Given that the simulation is designed to be reasonably accurate, players of *SimCity* should be able to transfer this knowledge to related management scenarios.

What we need are more example games like *SimCity* that are both absorbing and afford deep learning of complex systems. In this chapter we have argued that this will not be easy to accomplish because the constraints of domain knowledge, emotions, and games are more frequently incompatible than they are aligned. However, rather than giving up trying, researchers need to conduct the systematic mappings between the systems and to perform the detailed behavioral, cognitive, and social task analyses. The world of games has not only captured the lives of the younger generations but has also penetrated adults of all ages. It is an empirical question whether it will be possible to smuggle deep knowledge, strategies, and skills into the commercial games that are so engaging and entertaining. It is also an empirical question whether serious deep games will yield higher learning gains than alternative advanced learning environments.

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