

(RUNNING HEAD: Intelligent Tutoring in Virtual Environments)

## **CHAPTER 49:**

### **Intelligent Tutoring and Pedagogical Experience Manipulation in Virtual Learning Environments**

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#### **1 Introduction**

Modern virtual environments provide new and exciting opportunities for the learning of complex skills. Rapid progress in the commercial game industry, as well as in computer graphics, animation, and artificial intelligence research, has produced immersive environments capable of simulating experiences that can closely resemble reality. Educators and learning scientists have grasped these opportunities, motivated by the prospect of providing safe, authentic practice environments for real-world skills not previously within the scope of computer-supported learning. Greater realism and more immersion seem to be in harmony modern instructional design methodologies and theories of learning, such as situated learning (Brown, Collins, & Duguid, 1989):

We argue that approaches such as cognitive apprenticeship that embed learning in activity and make deliberate use of the social and physical context are more in line with the understanding of learning and cognition that is emerging from research (p. 32).

A tenet of situated cognition is that knowledge should be learned in its context of use as well as within the culture of its practice. Computer-based learning environments that seek to replace traditional paper-based homework assignments tend to be based on the “culture of school” rather than the more real-world cultural contexts discussed in the situated

learning literature, and thus rarely leverage the full capabilities of a computer to simulate these contexts. Virtual learning environments (VLEs), on the other hand, hold the potential to provide learners with greater authenticity and clearer connections to real-world applications of skills they are acquiring.

However, there is a natural tension between the realism in virtual learning environments (VLEs) and efficient, robust learning. For example, real-world skills that may take months or years to apply (such as building a home) may not require faithful representation of time in a computer simulation (such as waiting 2 weeks for the delivery of materials). Relying exclusively on high fidelity and immersion therefore limits a VLE's ability to actually promote learning. Numerous studies have shown that learning is sub-optimal, sometimes even hindered, when pure discovery and trial-and-error are used as the primary means for skill acquisition (Mayer, 2004; Kirschner, Sweller, & Clark, 2006). Guidance is therefore critical to avoid these pitfalls, especially for novices. Support can come from a variety of sources, of course, such as instructors, peers, carefully designed instructional materials, or even from within the learning environment itself. Our focus here is on the latter – i.e., how we might scaffold learning automatically and from within a virtual learning environment. This chapter summarizes principles that have emerged from studies of human and computer tutors as well how artificial intelligence (AI) and intelligent tutoring system (ITS) technologies can be applied to the problem of providing guidance in immersive and virtual learning environments.

## **2 Human and computer tutoring**

Students working one-on-one with expert human tutors often score 2.0 standard deviations – roughly two grade levels – higher than students in a conventional classroom

(Bloom, 1984). In contrast, the very best intelligent tutoring systems achieve learning gains of about 1.0 standard deviations (Anderson, Corbett, Koedinger, & Pelletier, 1995; VanLehn et al., 2005). The best computer-aided instructional systems – computer tutors that do not use AI techniques – produce learning gains of about .4 standard deviations (Niemiec & Walberg, 1987). Unfortunately, a precise answer to the question of why tutoring is more effective than other forms of instruction has remained elusive. Most hypotheses tend to focus either on the behaviors of the tutor – that learning occurs because of expert execution of tutoring tactics – or of the student – that learning occurs when the student makes deep contributions during a tutoring session. Each of these perspectives has implications for how intelligent tutors should behave in virtual environments and so in this section, we take a brief look at both of these hypotheses and the empirical evidence supporting them.

## **2.1 Why is tutoring effective?**

A popular claim for the effectiveness of tutoring is that human tutors are able to adapt, and thus individualize instruction to fit the needs of the particular student being tutored. These adaptations can be made in response to a variety of student traits including those involving the knowledge state of the student, or of the affective (emotional) state. For example, some expert human tutors implement mastery loops that involve the repeated assignment of problems that test a particular skill (or set of skills) until the student has confidently demonstrated competence (Bloom, 1984). Another tactic is to select or formulate problems in ways that will appeal to and motivate the student (Lepper et al., 1993). Assigning an easier problem when a student's confidence is low is an example of a tutoring tactic in this category. Human tutors also implement different

tactics based on student traits. For example, the policy of immediate feedback is a well-documented tactic applied by both human and computer tutors that increases learning efficiency (Merrill, Reiser, Ranney, & Trafton, 1992; Anderson et al., 1995), but may hinder students' self-assessment and self-correction skills (Schooler & Anderson, 1990). Immediate feedback is considered individualized in the sense that students' own specific sets of correct and incorrect actions determine what kind of feedback they receive – it is rare that two students will receive exactly the same tutorial interventions. Like problem selection, the content and timing of tutoring feedback can be based on the knowledge state of the student or on affective traits. Lepper et al. (1993) document a variety of lower level tutoring tactics intended to manage affect, such as maximizing success (through praise) and minimizing failure (via commiseration).

Some have argued that the best tutors balance the need for active participation of the student with the provision of guidance (Merrill et al., 1992). This means the student does as much of the work as possible while the tutor provides just enough feedback to minimize frustration and confusion. Also, effective tutoring has been found to have less to do with didactic explanations by the tutor and more to do with the interaction between the tutor and student. Chi, Siler, Jeong, Yamauchi, and Hausmann (2001) conclude that “students' substantive construction from interaction is important for learning, suggesting that an ITS ought to implement ways to elicit students' constructive responses” (p. 518). It is a common pattern in ITS research to first identify effective learning events and patterns in human tutoring, then attempt to emulate them in an ITS.

## **2.2 Intelligent tutoring systems**

Given that research on intelligent tutoring is often inspired by empirical studies of human tutors, it is not surprising that computer tutors share many similarities with human tutors (Merrill et al., 1992). For example, when a student reaches an impasse, human and intelligent computer tutors both use similar approaches to help the student overcome the impasse: both monitor student reasoning and intervene to keep the student on a productive path. A major limitation for early generation tutoring systems was that they interacted with the learner primarily through graphical user interface gestures, such as menu selections, dragging-and-dropping, and so on. For example, in the Andes physics tutoring system (VanLehn et al., 2005), students draw force vectors on diagrams and enter equations into text fields. Andes provides immediate flag feedback by coloring correct actions green and incorrect actions red. Solicited help is available that allows the student to ask why an action is wrong or for advice on taking the next step. Andes implements model tracing, an algorithm originally appearing in the Cognitive Tutors from Carnegie Mellon University (Anderson et al., 1995). Model tracing tracks a learner step by step through a problem solving space, comparing the observed actions to those indicated by an expert model of the targeted skill, and delivering feedback according to some pedagogical model or policy. Immediate feedback with solicited follow-up help is one such policy.

Human tutors have an advantage over computer tutors in that a much larger space of tutorial interventions are possible. For example, some important differences that distinguish human tutors arise from subtle cues from facial expressions, body language, conversational cues, or the simple use of dialogue (Fox, 1993). Given the 1 sigma “gap” between the effectiveness of expert human tutors and the best computer tutors, it is no

surprise that a great deal of research in the last decade has gone into endowing computer tutors with more of the “features” of human tutors in the hope of narrowing the effect size difference. The use of interactive dialogue represents a major research focus over the last decade. Many such systems attempt to leverage the expressivity of natural language input and dialogue to remediate flawed conceptual knowledge (Graesser, VanLehn, Rose, Jordan, & Harter, 2001) while others have used dialogue to encourage metacognitive and reflective thinking on problem solving (Core et al., 2006; Peters, Bratt, Clark, Pon-Barry, & Schultz, 2004; Katz, Allbritton, & Connelly, 2003). Just as dialogue opens up new avenues for tutorial intervention, so does research into pedagogical agents and virtual human instructors.

### **3 Considerations for intelligent tutoring in virtual environments**

Rickel and Johnson (1997), who were among the first to propose the use of intelligent tutoring in virtual reality environments, point out that much stays the same: students will still reach impasses, demonstrate misconceptions, and will benefit from the guidance and help of a tutor. They highlight new methods of interactions afforded by VLEs:

- The tutor can inhabit the environment with the student, thus providing increased potential for “physical” collaboration.
- Similarly, an embodied tutor can communicate nonverbally, through gestures and facial expressions, for example.
- A virtual reality environment allows students to be tracked in new ways, such as by their visual attention and physical movements.

Thus, the scope of tutorial interactions are greatly increased in VLEs, in both directions: in performing tutorial interventions and in the bandwidth available for monitoring the learner. Researchers have explored the ways in which virtual environments differ from more traditional computer-based learning environments that tend to be developed as substitutes for written homework. How well do traditional ITS approaches, such as those discussed in the previous section, map into tutoring in VLEs? What opportunities do VLEs make available that might enhance the effectiveness of an intelligent tutor? Here, we consider both directions: (1) how the advances from intelligent tutoring in traditional environments might be used to promote learning in VLEs, and (2) whether more advanced immersive technologies might contribute to closing the 1 sigma gap between human and intelligent tutoring.

We limit our consideration to those VLEs specifically constructed for the learning of cognitive skills that also include an underlying simulation of some real-world phenomenon. We also restrict ourselves to those environments that seek a reasonably high level of fidelity and realism. Thus, included in the discussion are virtual worlds that permit exploration from a first-person perspective, simulations of complex equipment (that include an interface modeled directly on actual equipment), and simulations of natural phenomena, such as social, biological, or meteorological phenomena.

### **3.1 Expanding the problem space: time and movement**

Many VLEs can also be classified as open learning environments. These are characterized by a greater amount of learner control and are generally considered to be more appropriate for learning in ill-structured domains (Jonassen, 1997). Because of the large problem space in many VLEs, solving the plan recognition problem (monitoring,

understanding, assessing, etc.) is often a significant challenge for ITSs. Here, we highlight two key challenges: tutoring in real-time contexts and in environments that provide expanded freedom of student movement in a virtual space.

### **3.2 Tutoring in real-time environments**

For problem solving tasks that are not time-constrained (e.g., solving algebra equations), computer-based learning environments typically wait for the learner to act. This stands in contrast to many domains targeted by VLEs that require real-time thinking, decision-making, and acting. Ritter and Feurzeig (1988, p. 286) were among the earliest to wrestle with the problems of tutoring in a real-time domain and highlight three major differences:

- The knowledge acquisition problem is more complicated since experts tend to “compile” their knowledge for efficient execution.
- Diagnosing errors is more complicated because time is typically not available to ask the student questions during practice.
- Assessing performance and conveying feedback is best done after task completion to avoid the risk of interrupting the learner (see Chapter 43-Lampton).

The knowledge acquisition problem is not magnified only by constraints related to real-time processing, but also by the nature of ill-structured domains in general (Lynch, Ashley, Alevan, & Pinkwart, 2006), which are common domain targets of VLEs. Diagnosis of errors and assessment of performance are similarly not unique to real-time domains, but are nonetheless more complicated because of time constraints during practice. Time-constrained problem solving often goes hand-in-hand with dynamic



learning environments – i.e., as time moves forward while the student deliberates, the state of the world may change in favorable or unfavorable ways. Here, we review several approaches to dealing with these challenges in terms of how ITSs have been implemented to support learning.

Ritter and Feurzeig (1988) describe TRIO (Trainer for Radar Intercept Officers), an ITS built to train F-14 interceptor pilots and radar operators to support the real-time decision-making tasks involved with air defense and collaboration. The system presents the learner with radar displays and flight instruments that provide both needed information and the ability to take actions in the simulation. TRIO provides guidance in three ways:

- before practice: demonstrations of expert performance
- during practice: coaching support while the learner practices
- after practice: post-practice debriefing (after-action review)

These interventions are driven by a rule-based cognitive model of domain expertise (called the “TRIO Articulate Expert”) that is capable of performing the intercept tasks the learner is acquiring. TRIO intervenes with a learner only if mission critical mistakes are being made (or about to be made), and leaves most feedback for the post-practice reflective period. This is a typical policy for ITSs operating in real-time domains given the risks of competing for the working memory of a learner. The Articulate Expert focuses on finding the appropriate intermediate goals throughout execution of the task and uses these to help the student learn what went wrong, and what should be done. The model is flexible enough to represent multiple solutions to a given problem.

Roberts, Pioch, and Ferguson (1998) adopted a similar approach in the development of TRANSoM (Training for Remote Sensing and Manipulation), an ITS for the training of pilots of underwater remotely operated vehicles (ROVs). Just as in TRIO, demonstrations, guided practice, and reflection also play key roles. Because of the real-time nature of the task, TRANSoM also attempts to simultaneously avoid distracting the learner while preventing session-killing errors from occurring. A key aspect to ROV operation is the maintenance of a mental model of the vehicle itself. This is a challenge given the limited inputs regarding the ROV's status (which is true in reality). To increase the chances of being nonintrusive, TRANSoM applies two techniques. First, all coaching support is delivered verbally so the visual modality is not in competition with the learner. Second, although unsolicited help is delivered in a manner similar to TRIO (when there is deviation from an expert solution path), students are also given the chance to ask for guidance when they feel they need it (i.e., solicited help). Among other lessons learned, Roberts et al. (1998) suggest that the use of discourse cues, short utterances, and the simultaneous use of directive visual cues along with verbal feedback would increase the chances of a verbal feedback being effective in a VLE.

### **3.3 Tutoring in open-movement environments**

To promote the feelings of learner control and freedom, many VLEs, especially those that are game-based, tend to allow free movement within a virtual world. This is consistent with the motivation for building open learning environments. It is typical in this category of VLEs to give the learner control of an avatar or vehicle to maneuver around in a virtual world. Usually done from a first-person perspective, it allows the learner to make choices like what to explore, when, and for how long. The problem for an

ITS in these environments is twofold. First, if the skill being practiced is directly related to the movements of the learner's avatar, it must be determined at what level of action the ITS should react. For example, does a turn in one direction represent an intention to move in that direction? Second, to what extent physical/motor skills transfer to the real world from virtual environments is an open question. Thus, most ITSs that permit free movement do so in order to maximize the learner's feeling of freedom and independence, and less because it contributes to the acquisition of some underlying cognitive or physical skill.

Very few ITSs precisely track how learners maneuver in a virtual environment. Most systems observe only gross physical movements (from area to area) and interact when issues arise related to the events of the game in those physical areas. One exception is the Collaborative Warrior Tutoring system (Livak, Heffernan, & Moyer, 2004), an ITS that tracks physical movements in a 3D, first-person shooter environment for the learning of tactical skills and military operations on urban terrain (MOUT; see Chapter 79-Livingston). Through the use of a cognitive model of room and building clearing skills that inspects the dynamically changing environment represented in the 3D world, the ITS is able to assess the learner's movements (including buggy knowledge) and give hints and feedback on the fly. These interventions come as text overlaid on the view of the virtual world alongside communications between characters. The model of expert performance is also used to drive the behaviors of computer-controlled characters in the environment.

Most other ITSs that permit free movement in a virtual world do not track movements at this fine-grained level. For example, in the Tactical Language and Culture

Training System (TLCTS) mission environment (Johnson, Vilhjalmsson, & Marsella, 2005), the learner is given game objectives and is free to move around an Iraqi village to achieve them. This requires visiting a variety of locations in the village (e.g., café) and interacting with locals in culturally appropriate ways through Arabic speech and gestures. This is similar to the approach taken in the narrative-based learning environment Crystal Island (Mott & Lester, 2006). In this system, the learner plays the role of scientist on an island where several of the inhabitants have become ill from an infectious disease. The learner must move around the island interviewing people, collecting evidence, and running tests. As in TLCTS, actual movements in the environment are important to the extent that they represent decisions – for example, if the learner walks towards a research station with a sample, it is reasonable to conclude she or she intends to test it for contamination.

### **3.4 Expanding the space of intelligent tutoring interactions**

As discussed, VLEs that are open tend to provide a much larger problem solving space than more traditional computer-based learning environments. Not only does this provide more freedom for the learner, but also for the ITS to perform a wider array of pedagogically motivated interactions. In this section we discuss two of these opportunities: through the use of pedagogical agents and via dynamic manipulation of the learning environment in ways that promote learning, sometimes called pedagogical experience manipulation.

#### **3.4.1 Pedagogical agents**

Artificial intelligence research into the development of intelligent, communicative agents and virtual humans has led to interdisciplinary research on natural

language processing, emotional modeling, gesture modeling, cultural modeling, and more (Cassell, Sullivan, Prevost, & Churchill, 2000; Swartout et al., 2006). Since people tend to treat human-like computer characters as they would humans (Reeves & Nass, 1996), there is potential for learners to “bond” more with intelligent tutors that express themselves through a human-like avatar. Previously in this chapter we discussed the 1 sigma “gap” between the best ITSs and expert human tutors, and how dialogue-based tutoring systems represent one attempt to bridge this gap. By endowing ITSs with features similar to those used by human tutors, the hypothesis is that this gap can be narrowed. For example, facial expressions might be used to express concern or approval, among other emotions, all of which are potentially useful as indirect feedback. Pedagogical agents tend to serve in one of two roles. The first is in the role of a coach or tutor with the goal of supporting learning through explicit guidance and feedback. The second is when the pedagogical agent assumes a role in an underlying narrative or story playing out in the virtual environment.

A wide range of pedagogical agents have been developed that play the role of tutor or coach (Clarebout, Elen, Johnson, & Shaw, 2002; Person & Graesser, 2002). Most provide hints and feedback to a learner during some problem solving task, provide explanations, communicate verbally and nonverbally, and seek to provide “just-in-time” support. Steve (Soar Training Expert for Virtual Environments), one of the earliest pedagogical agents, possessed all of the traditional capabilities of ITSs (delivered feedback, explanations, gave hints, etc.), but also had the ability to lead the learner around the virtual environment, demonstrate tasks, guide attention (through gaze and pointing), and play the role of teammate (Rickel et al., 2002; Rickel & Johnson, 1997).

Using animation, sound, and dialogue techniques, pedagogical agents can also attempt to manage the learner's affective state through encouragement and motivational techniques. For example, in the MIMIC system (Multiple Intelligent Mentors Instructing Collaboratively), an emotional instructional agent has been implemented that will express confusion, disapproval, excitement, encouragement, pleasure, and more (e.g., Baylor & Kim, 2005).

In narrative-based learning environments, pedagogical agents have the opportunity to be "part of the story" by assuming some role in the underlying narrative being played out in the environment. For example, in the Mission Rehearsal Exercise (MRE) system (Swartout et al., 2006), the learner, playing the role of a young lieutenant, is placed in a situation in which one of his platoon's Humvees has been in an accident with a civilian car. The sergeant in the scenario has knowledge of how to resolve the crisis and will give guidance should the learner need it, such as pointing out the negative aspects to a particular order (e.g., "Sir, our troops should not be split up."). A similar solution is used in TLCTS in endowing an accompanying sergeant with coaching ability, but making only solicited help available (Johnson et al., 2005). In recent versions of TLCTS, tutoring by the accompanying aide has been curtailed, as it was found that some learners got the false impression that only a limited number of choices were available, namely those that the aide recommends. Instead, tutoring support is provided through the characters in the game, by their reactions to the learner, and at times by the leading questions that they ask of the learner. This approach is inspired by the tactics that good human role players employ in role playing exercises, at training centers such as the Army's National Training Center. Crystal Island also provides all of its tutoring support

through the characters in the game (Mott & Lester, 2006) as well as affective support through empathetic characters (McQuiggan, Rowe, & Lester, 2008).

Empirical research on pedagogical agents is mixed in terms of how well they close the 1-sigma gap between computer and human tutors (Clarebout et al., 2002). Moreno, Mayer, and Lester (2000) found that the simple presence of an animated agent did not impact learning, but that speech (over text) led to improved retention and transfer in learning. The same study also showed that interactive dialogue was superior to more didactic utterances by the agent, which is consistent with studies of dialogue-based ITSs that do not use pedagogical agents (Graesser et al., 2001). In research aimed at understanding how pedagogical agents can go beyond only possessing domain knowledge, Baylor & Kim (2005) found evidence that agents playing both a motivator and expert role simultaneously (which they refer to as a “mentor”) outperformed agents in each of these roles alone in the ill-defined domain of instructional planning.

Wang et al. (2007) found that a key determiner of the effectiveness of a pedagogical agent is the extent to which the agent employs socially appropriate tactics that address learner “face”, consistent with the Politeness Theory of Brown and Levinson (1987). Learners who interacted with a pedagogical agent that employed politeness tactics achieved greater learning gains than learners who interacted with an agent that did not employ such tactics, and the effect was greatest among learners who expressed a preference for tutorial feedback delivered in a polite, indirect way. Wang has since replicated these results with TLCTS, using politeness strategies delivered via text messages. These studies suggest that (a) the manner in which the agent interacts with the learner determines its impact on learning; (b) the effect varies with the individual

characteristics of the learner, and (c) socially appropriate tactics can affect learning even without an animated persona.

Studies involving pedagogical agents generally show that learners prefer having a pedagogical agent to not having one, but more evidence needs to be collected to determine their actual value in promoting learning beyond what disembodied ITSs are able to do.

### **3.4.2 Pedagogical experience manipulation and stealth tutoring**

A VLE's underlying simulation provides more subtle opportunities to promote learning beyond explicit guidance. In most VLEs, many forms of implicit feedback already exist which mirror feedback one can observe in real environments. For example, if a basketball is shot, implicit feedback comes from the visual evidence that the ball flies through the hoop or bounces off the rim. In a virtual environment, it may be that different events and behaviors may be more appropriate for learning at different times. It may be pedagogically beneficial to override a simulation such that it establishes ideal conditions for learning or produces implicit feedback that meets an individual learner's needs. In the basketball example, it may be better for the simulation to have the ball go in the hoop if the goal is to give the learner practice in playing in a tight game (assuming the basket would make the score closer). In this section, we briefly describe two such approaches: experience manipulation and stealth tutoring.

There are at least two strategies available for intelligent manipulation of a learner's experience in a VLE that can promote learning. The first is through the amplification or dampening of implicit feedback. For example, in simulations with virtual humans, it is possible to tweak their behaviors to achieve certain pedagogical objectives.



For example, if a learner commits a cultural error, such as mentioning a taboo subject, it may be productive to have the character overreact to that error to support the learner's recognition of the mistake. If the implicit feedback is amplified in this way, the ITS would be supporting the metacognitive skill in the learner of recognizing that an error was made, which is a critical early step in acquisition of intercultural skills (Lane, 2007). Similarly, if a learner has repeatedly demonstrated knowledge of a given cultural rule, it may make sense to minimize time spent related to that already mastered material. This could be played out by virtual humans with shorter utterances and dampened visual reactions when applicable.

A second category of experience manipulation lies in the actual dynamic modification of the state of the simulation in ways that establish appropriate conditions for learning. Although modification of implicit feedback can be used in this way, there are other means. For example, in the Interactive Story Architecture for Training (ISAT) system, the learner is guided through plot points which are selected based on an evolving learner model (Magerko, Stensrud, & Holt, 2006). The version of ISAT that runs in the domain of combat medic skills will manipulate the environment in ways that address the needs expressed by the learner model. For example, if a learner has difficulty identifying the proper order in which to treat multiple injured soldiers, ISAT is capable of adapting the injured soldiers' injuries and behaviors such that they test the specific weaknesses of the learner. In the combat medic domain, ISAT may adjust the damage an explosion inflicts on victims of an attack or tweak their behaviors resulting from sustained injuries – for example, rolling around on the ground or yelling. These examples of experience

manipulation are intended to establish conditions for learning and allow the learner the chance to practice the right skills at the best times within a VLE.

Stealth tutoring, a specific kind of experience manipulation, focuses on methods of conveying tutor-like explicit guidance from within the VLE. Given that explicit help comes with the risk of learner dependence on it, there may be times when covert support may be preferable so that a learner is not aware help is being given. Crystal Island, and the underlying narrative and tutorial planning system U-Director, demonstrate stealth tutoring in a particularly elegant way (Mott & Lester, 2006). If the system detects that a learner is wandering around the island and failing to make progress, the underlying planning model will decide to direct the nurse character to share her opinion that some of the food on the island might be making people sick. This “hint” comes only after the detection of floundering and in an entirely plausible way (via a character who is concerned about the infectious disease). Of course, an accompanying risk of providing covert support is that, if detected by the learner, self-efficacy and confidence may subsequently suffer.

Narrative-based learning environments make this kind of support possible. A similar method is used by the virtual human sergeant in the MRE when his initiative is set to “high” – he will more openly share his opinion regarding what needs to be done at any given time (Rickel et al., 2002; Swartout et al., 2006). Although these approaches both rely on virtual characters (and thus fit under the space of pedagogical agent interactions), other opportunities exist to give hints and guidance indirectly through the environment. Care must be taken, however, as with any pedagogical support approach, that the learner does not become dependent on this assistance.

## **4 Conclusions**

In this chapter we described many of the issues facing designers of intelligent tutoring systems for virtual learning environments. Specific challenges arise from the nature of domains that VLEs make accessible, such as tutoring for real-time skills and the problem of understanding student actions in open learning environments. Expertise is generally harder to capture and encode in such domains, when compared to domains that involve forms of symbol manipulation and that are less dynamic. Research into automatic approaches to acquiring domain knowledge in VLEs would support the longer term integration of ITSs. We also described the role of pedagogical agents and how they can be used to promote learning in VLEs. Although current empirical evidence for the use of pedagogical agents remains unclear, they have been found to have many appealing properties for learners and to be beneficial in ways other than just promoting learning (e.g., motivation). Pedagogical agents can also participate in an underlying narrative, and thus provide more opportunities for tutorial intervention. We described pedagogical experience manipulation in terms of how it can be used to adjust implicit feedback to promote a learner's recognition of success or failure and how it can be used to dynamically establish ideal conditions for learning. These new capabilities and new tactics may support "closing the gap" between expert human tutors and computer tutors, but significantly more empirical research is needed to find out.

Virtual learning environments with intelligent tutoring capabilities are beginning to be adopted on a widespread basis. For example, TLCTS learning environments are being used by tens of thousands of military service members (Johnson 2007), and additional learning environments are being developed for non-military use. Because

these learning environments are instrumented and log all learner actions, they are an excellent source of data to assess the effectiveness of tutoring techniques in VLEs.

Several key questions remain unanswered in the literature regarding the use of ITSs in modern VLEs. For example, how distracting is explicit feedback? How do different modalities compare with respect to distraction? As far as pedagogical experience manipulation, what is the proper balance between narrative control and explicit tutorial control? What other kinds of guidance are possible through stealth techniques, such as difficulty management and task selection? When are explicit measures required and how do they compare when delivered via stealth approaches? What are the risks of stealth guidance and experience manipulation on learners with respect to confidence, self-efficacy, and help-seeking skills?

Modern VLEs make realistic practice in a computer-based environment possible, and answers to these kinds of questions will have great impact on how effective VLEs may become. There is no end in sight to the immersive potential for virtual environments – it is important to remember, as Rickel and Johnson (1997) pointed out, that learners will continue to exhibit misconceptions and hit impasses. In order to maximize the teaching power of modern VLEs, it will be important to continue to consider these empirical questions, understand the accompanying risks, and create technological advances that adhere to principles of effective learning.

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