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Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) are computerized learning environments that incorporate computational models in the cognitive sciences, learning sciences, computational linguistics, artificial intelligence, mathematics, and other fields that develop intelligent systems that are well-specified computationally. An ITS tracks the psychological states of learners in fine detail, a process called student modelling. The psychological states may include subject matter knowledge, skills, strategies, motivation, emotions, and other student attributes. An ITS adaptively responds with activities that are both sensitive to these states and that advance the instructional agenda. The interaction between student and computer evolves in a flexible fashion that caters to the constraints of both the student and the instructional agenda. This is a marked departure from a book or a lecture, which unfold in a rigid linear order and are not tailored to individual students.

The history of ITS was christened with the edited book by Sleeman and Brown (1982) entitled *Intelligent Tutoring Systems*. The contributors to the book were an interdisciplinary mixture of researchers in artificial intelligence, cognitive science, and education. There was the vision that learning could substantially improve by developing adaptive intelligent learning environments that took advantage of the latest advances in intelligent systems. By the early 1990's there were two conferences that directly focused on ITS development and testing: Intelligent Tutoring Systems and Artificial Intelligence in Education. A monograph by Woolf (2009) describes ITS architectures and many of the landmark contributions during the 30 history of the field.

Advances in ITS have progressed to the point of being used in school systems. One noteworthy example is the *Cognitive Tutors* developed by the Pittsburgh Science of Learning Center (Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger, Anderson, Hadley, & Mark, 1997; Ritter, Koedinger, Anderson, & Corbett, 2007). The Cognitive Tutors help students learn

algebra, geometry, and programming languages by applying learning principles inspired by the ACT-R cognitive model (Anderson, 1990). There is a textbook and curriculum to provide the content and the context of learning, but the salient contribution of the Cognitive Tutors is to help students solve problems. The Cognitive Tutors are now used in over 2000 school systems throughout the country and are among the methods accepted in the *What Works Clearinghouse*. According to Ritter, Anderson, Koedinger, and Corbett (2007), standardized tests show improvements over suitable control conditions and are particularly effective for the more challenging subcomponents of problem solving and use of multiple representations.

This chapter reviews the research on different classes of ITS. This includes a description of the computational mechanisms of each type of ITS and available empirical assessments of the impact of these systems on learning gains. However, before diving into the details of these major ITS advances, it is important to give some highlights on what we know about human tutoring, including the practice of human tutoring, relevant pedagogical theories, and empirical evidence for the effectiveness of human tutoring. Indeed, many ITS are built with the guidance of what human tutors and teachers know about effective pedagogy. The final section identifies some future directions for the ITS field to pursue.

What Do We Know about Human Tutoring?

Tutoring is the typical solution that students, parents, teachers, principals and school systems turn to when the students are not achieving expected grades and educational standards. Stakeholders are worried when a school is underperforming according to the criteria of *No Child Left Behind* because there are salient implications for teacher employment and salaries in addition to the more abstract concerns about the students' educational needs and the global image of the community. Human tutors step in to help under these conditions.

This section analyzes human tutoring from three questions. First, what is the nature of human tutoring in actual schools systems and the community? Second, what do the research studies reveal about the effectiveness of human tutoring on learning gains? Third, what are some common tutoring patterns when human tutors tutor “in the wild?”

Human Tutoring in the Wild

Human tutoring consists of one-to-one educational interventions with a human tutor. There are many different versions or purposes for human tutoring, including assignment assistance, instructional tutoring, and strategic tutoring (Hock, Pulvers, Deshler, & Schumaker, 2001). Instructional tutoring consists of direct instruction in such skills as literacy, mathematics and writing. Assignment assistance is supplemental to basic instruction and involves a tutor working with students who have difficulty completing course assignments. In strategic tutoring, students are taught to learn how to learn while they engage in classroom instruction and complete course assignments. Strategic tutoring combines instructional tutoring and assignment tutoring, with a particular focus on a learning strategy such as problem solving, summarization or questioning.

There can be a great deal of disagreement about who does the tutoring, the focus of the tutoring with respect to knowledge and skill, and even the intended clients or recipients of the tutoring. Under the most ideal conditions, human tutors are knowledgeable or skilled teachers or other adults who provide one-to-one support for students who need to improve in some academic area (Conley, Kerner, & Reynolds, 2005; Hock, et al., 2001; Pressley & McCormick, 1995; Tollefson, 1997). There is evidence that human tutors who are not expert and yet tutor in academic areas can actually do more harm than good. For example, special education teachers without specific academic expertise in areas of tutoring fail to help students develop the

knowledge and skills to become independent thinkers and learners in those areas (Carlson, 1985). Novice human tutors can fail to effectively engage their students, ignore important components of tutoring such as modeling or providing effective feedback, and even abandon research-based instruction in favor of personal views based on their own experiences with schooling, all despite the most intense training and monitoring (Hock, Schumaker, & Deshler, 1995)

So-called professional tutoring programs respond to the need for expert tutors by using certified teachers or by putting the tutors through intensive, specialized training (Slavin, Karweit, & Madden, 1989; Wasik, 1998; Wasik & Slavin, 1990). In a comparative review of tutoring programs using varying kinds of skilled personnel and differing kinds of training, including volunteers, it was found that the greatest impact on reading achievement comes from the use of certified professional teachers trained in specific tutoring interventions (Wasik & Slavin, 1990). Unfortunately, the most effective human tutoring program also was the most costly tutoring program. It is not uncommon in the research literature to see cost analyses accompanying research on human tutoring, with a similar finding reinforced each time: effective human tutoring requires expertise, but that expertise is almost always a formidable expense.

There is an obvious trade-off between the expertise of the tutor and the cost of professional human tutoring programs. In light of this tradeoff, there is a wide range of tutoring programs that employ community volunteers, college students, and student peers. To compensate for the lack of innate expertise with many human tutors, researchers embed tutoring scripts or lesson plans in the tutoring, provide extensive or scaffolded tutor training, or use a variety of multimedia resources to cue the tutors to do the right things at the right time. One of the most successful versions of this approach is the Charlottesville Volunteer Tutorial, popularly known as *Book Buddies* (Invernizzi, Rosemary, Juel, & Richards, 1997). *Book Buddies* is a joint

effort from the University of Virginia and the Charlottesville City Schools. Tutors in Book Buddies are community volunteers who tutor first grade students in emergent and early literacy. Tutors are provided a tutoring manual and are supervised in local schools by expert teachers and site coordinators. The content of the tutoring focuses on early reading skills including alphabetic knowledge, phonemic awareness, word recognition and fluency. The scripted nature of the program, along with the site-based supervision, has resulted in considerable consistency among the tutors in their implementation of the program. Researchers found that a minimum of thirty one-hour tutoring sessions was necessary to see gains in alphabetic knowledge, phoneme-grapheme knowledge, word recognition and concept of a word. Forty sessions yielded an even greater impact. The researchers compared the cost of the volunteer tutoring program with other school-based funded tutoring programs such as Reading Recovery. The volunteer tutoring program costs (e.g., program coordinator, on-site supervision of tutors, training manuals) was one-sixth the cost of school based funded programs while effect sizes for word recognition in Book Buddies far outpaced effect sizes using professionally trained teachers in more expensive programs. Proponents cite these factors (i.e., low cost and high impact) as key reasons to use volunteer tutors working under carefully structured and scripted conditions rather than spending lots of money to train professional tutors.

One limitation of many human tutoring programs concerns their relatively narrow focus. Book Buddies, for example, involves tutoring with several hundred first graders at a time (Invernizzi, et al., 1997). Strategic tutoring, which employs highly trained tutors working with special education children, often engages 30 or fewer children at a time (Hock, et al., 2001; Vellutino, et al., 1996). In one notable example in which Book Buddies was scaled up and implemented in a more complex school setting, the Bronx, tutors were unable to move students

to a reading level necessary for them to succeed in school, compared with non-participating peers (Meier & Invernizzi, 2001). In a recent review of volunteer tutoring programs for elementary and middle school children, 21 studies using 28 different cohorts of students revealed positive effects on achievement but only with very basic sub-skills in reading, such as phonemic awareness, word recognition and fluency (Ritter, Barnett, Denny, & Albin, 2009). Noteworthy in this meta-analysis was the finding that human tutoring programs, as they were construed, did not have a significantly different impact on comprehension or in other academic areas like mathematics. Not surprisingly, there was little if any evidence of transfer of skill from human tutoring in basic literacy skills into other academic areas like mathematics or science. In short, for all of the expense and effort that often goes into human tutoring, both professional and volunteer, the outcomes have been promising, but extremely limited in the population served and overall impact.

Learning Gains with Human Tutoring

The studies cited above present a mixed picture of the impact of human tutoring on learning. One of the landmark early assessments of human tutoring was the meta-analysis conducted by Cohen, Kulik, and Kulik (1982) who reported learning gains of approximately 0.4 sigma when compared to classroom controls and other suitable controls. A sigma is a measure in standard deviation units that compares a mean in the experimental treatment to the mean in a comparison condition. According to Cohen (1992), effect sizes of 0.20, 0.50, and 0.80 are considered small, medium, and large, respectively, so the .088 effect size would be considered large. Therefore, a 0.4 sigma is considered a medium effect size.

Many of the tutors in the documented research on tutoring include unskilled tutors. Unskilled tutors are defined in this chapter as tutors who are not experts on subject matter

knowledge, are not trained systematically on tutoring skills, are not certified, and are rarely evaluated on their impact on student learning. Unskilled tutors are paraprofessionals, parents, community citizens, cross-age tutors, or same-age peers. In spite of their lack of training and skill, they nevertheless improve learning under some conditions. There are many possible explanations of these learning gains from tutors who are unskilled. Perhaps they have sufficient intuitions to detect deficits in the student and can make sensible recommendations on how the student can improve. Perhaps there is something about one-on-one conversation with another human that helps motivation and learning (Graesser, Person, & Magliano, 1995). Available evidence suggests that the expertise of the tutor does matter, but the evidence is not strong. For example, collaborative peer tutoring shows an effect size advantage of 0.2 to 0.9 sigma (Johnson & Johnson, 1992; Mathes & Fuchs, 1994; Slavin, 1990; Topping, 1996), which appears to be slightly lower than older unskilled human tutors. Peer tutoring is a low-cost effective solution because expert tutors are expensive and hard to find. Unfortunately, systematic studies on learning gains from expert tutors are few in number because the tutors are expensive, they are difficult to recruit in research projects, and they tend to stay in the tutoring profession for a short amount of time (Person, Lehman, & Ozbun, 2007). However, available studies report effect sizes of 0.8 to 2.0 (Bloom, 1984; Chi, Roy, & Hausmann, 2008; VanLehn et al., 2007), which is presumably higher than other forms of tutoring. Nevertheless, there clearly needs to be more research on the impact of tutoring expertise on student learning in mathematics, reading literacy, science, and self-regulated learning strategies.

The impact of tutoring on learning is not determined entirely by the tutor, of course, because there are also constraints of the student and the student-tutor interaction. Constructionist theories of learning have routinely emphasized the importance of getting the student to generate the knowledge rather than expecting an instruction delivery system to provide all of the information (Bransford,

Brown & Cocking, 2000; Mayer, 2009). Students learn by expressing, doing, explaining, and being responsible for their knowledge construction, as opposed to being passive recipients of exposure to information. We know, for example, that the tutors in the same-age and cross-age collaborations tend to learn more than the tutees, even when they start with essentially the same level of mastery (Cohen et al., 1982; Mathes & Fuchs, 1994; Rohrbeck, Ginsburg-Block, Fantuzzo, & Miller, 2003).

The obvious question that learning scientists have been asking over the years is why tutoring is effective in promoting learning? We believe that the best approach to answering this question is to analyze the tutoring process and to explore what it is about the process that lends itself to learning (see Graesser, D'Mello, & Cade, in press). But what are these processes? A number of studies have performed a very detailed analysis of the tutoring session structure, tasks, curriculum content, discourse, actions, and cognitive activities manifested in the sessions and to speculate how these might account for the advantages of tutoring (Chi, Roy, & Hausmann, 2008; Chi et al., 2001; Graesser & Person, 1994; Graesser, Person, & Magliano, 1995; Hacker & Graesser, 2007; Lepper, Drake, & O'Donnell-Johnson, 1997; McArthur, Stasz, & Zmuidzinas, 1990; Merrill, Reiser, Merrill, & Landes, 1995; Person & Graesser, 1999; 2003; Person, Kreuz, Zwaan, & Graesser, 1995; Shah, Evens, Michael, & Rovick, 2002; VanLehn et al., 2003). We believe these detailed analyses have considerable promise. At the same time, however, we believe it is not adequate to stop at that point because there needs to be an experimental approach that assesses causal relations between tutoring practice and learning. One needs to manipulate the tutoring activities through trained human tutors or computer tutors and to observe the impact of the manipulations on learning gains (Chi et al., 2001, 2008; Graesser, Lu et al., 2004; Litman et al., 2003; VanLehn et al., 2003,

2007). Manipulation studies allow us to infer what characteristics of the tutoring directly cause increases in learning gains, barring potential confounding variables.

Tutoring Strategies and Processes

The studies referenced have documented the strategies and processes of tutoring in diverse areas and tutors with diverse expertise. For example, Graesser and Person analyzed the discourse patterns of 13 unskilled tutors in great detail after analyzing over 100 hours of tutoring sessions (Graesser, & Person, 1994; Graesser et al., 1995; Person & Graesser, 1999). Person et al.'s (2007) meta-analysis of accomplished tutors revealed that the sample sizes of expert tutors have been extremely small ($N < 3$) in empirical investigations of expert tutoring and often the same expert tutors are used in different research studies. Person et al. (2007) analyzed 12 tutors who were nominated by teachers in the Memphis community who were truly outstanding.

Unfortunately, these studies that analyzed the tutoring process in detail did not have outcome scores. There is a large void in the literature on detailed analyses of human tutorial dialogue that are related to outcome measures and that have a large sample of tutors. There are also practical limitations that present serious obstacles to collecting such data. The subject matters of the tutoring sessions are difficult to predict in advance so it is difficult to proactively identify suitable pre-test and posttest measures from normative testbanks. There is also a large attrition rate for both tutors and students. Nevertheless, these tutoring corpora can be analyzed to identify the tutoring processes.

A number of strategies that are not implemented very often by either expert or novice tutors according to the above studies that have investigated the tutoring process. Human tutors are not prone to implement sophisticated tutoring strategies that have been proposed in the fields of education, the learning sciences, and developers of ITSs (Graesser et al., 1995; Graesser,

D'Mello, & Person, 2009; Person et al., 1995). Tutors rarely implement pedagogical techniques such as *bona fide* Socratic tutoring strategies (Collins et al., 1975), modeling-scaffolding-fading (Rogoff & Gardner, 1984), Reciprocal Teaching (Palincsar & Brown, 1984), frontier learning (Sleeman & Brown, 1982), building on prerequisites (Gagne, 1985), or diagnosis/remediation of deep misconceptions (Lezgold et al., 1992). Tutors do not have a deep understanding of what the student knows, i.e., the student model, so their responses run the risk of not being on the mark in advancing learning. Tutors have only an approximate understanding of the students' profile so there is an inherent limitation in how well they can adapt effectively.

Graesser and Person's analyses of tutorial dialogue uncovered a number of frequent dialogue structures that presumably have some potential in advancing learning (Graesser & Person, 1994; Graesser et al., 1995; Graesser, Hu, & McNamara, 2005). These structures are also prominent in the work of other researchers who have conducted fine-grained analyses of tutoring (Chi et al., 2004; Graesser, Hu, & McNamara, 2005; Litman et al., 2006; Shah et al., 2002). The following dialogue structures are prominent: (a) a curriculum script with didactic content and problems (i.e., difficult tasks or questions), (b) a 5-step Tutoring Frame, (c) Expectation and Misconception Tailored (EMT) dialogue, and (d) Conversational Turn Management.

(a) Curriculum script. The tutor tries to cover a curriculum with substantive content and a set of problems that address the content. The content can be presented in a mini-lecture, hopefully at the right time for the individual learner. The problems are tasks, activities, and difficult questions that reveal whether the student is understanding. Tutors tend to present the mini-lectures and problems in a rigid way rather than tailoring to the individual learner.

(b) 5-Step Tutoring Frame. After a problem or difficult main question is selected to work on, the problem is solved through an interaction that is structured by a 5-Step Tutoring Frame. The 5 steps are: (1) Tutor presents problem, (2) Student gives an initial answer, (3) Tutor gives short feedback on the quality of the Student's initial answer, (4) the Tutor and Student collaboratively improve on the answer in a turn-by-turn dialogue that may be lengthy, and (5) the Tutor evaluates whether the Student understands (e.g., asking "Do you understand?" or testing with a follow-up task). This 5-step tutoring frame involves collaborative discussion, joint action, and encouragement for the student to construct knowledge rather than merely receiving knowledge.

(c) Expectation and Misconception Tailored (EMT) Dialogue . Human tutors typically have a list of expectations (anticipated good answers, steps in a procedure) and a list of anticipated *misconceptions* associated with each main question. They want this content covered in order to handle the problem that is posted. The tutor guides the student in articulating the expectations through a number of dialogue moves, namely *pumps* ("What else?"), *hints*, *questions* to extract specific information from students, and *answers* to students' questions. The correct answers are eventually covered and the misconceptions are hopefully corrected.

(d) Conversational Turn Management. Human tutors structure their conversational turns systematically. Nearly every turn of the tutor has three information slots (i.e., units or constituents). The first slot of most turns is feedback on the quality of the learner's last turn. This feedback is either positive (*very good, yeah*), neutral (*uh huh, I see*), or negative (*not quite, not really*). The second slot advances the interaction with either prompts for specific information, hints, assertions with correct information, corrections of misconceptions, or answers to student questions. The third slot is a cue for the floor to shift from the tutor as the speaker to the learner.

For example, the human ends each turn with a question or a gesture to cue the learner to do the talking.

Student Modeling. One of the central questions is how well the tutor can track the psychological states of the student as they implement these strategies. Available evidence suggests that human tutors are not able to conduct student modeling at a fine-grained level. They can perform approximate assessments, but not fine-grain assessments. This of course limits how well humans can adaptively respond. Moreover, there is the possibility that computers might show advantages over humans to the extent that computers can accurately conduct student modeling and generate intelligent responses.

Consider, for example, how well human tutors can track knowledge states of learners. Graesser, D'Mello, and Person (2009) have documented some of the illusions that typical human tutors have about cognition and communication. These illusions may limit optimal learning. According to the *illusion of grounding*, the tutor mistakenly believes that the speaker and listener have shared knowledge about a word, referent, or idea being discussed in the tutoring session. A tutor should be skeptical of the student's level of understanding and trouble-shoot potential communication breakdowns in common ground between the tutor and student. According to the *illusion of feedback accuracy*, the tutoring mistakenly believes that the feedback is accurate when the student indicates their understanding of the subject matter. For example, tutors incorrectly believe the students' answers to their comprehension gauging questions (e.g., Do you understand?). According to the *illusion of student mastery*, the tutor believes that the student has mastered much more than the student has really mastered. For example, the fact that a student expresses a word or phrase does not mean that the student understands an underlying complex idea. According to the *illusion of knowledge transfer*, the tutor believes that the information they express is accurately

transmitted to the mind of the student. In fact, the student absorbs very little. These illusions threaten to fidelity of student modelling in human tutoring, so there is the fundamental question of how useful their dialogue moves will be in advancing learning. A more realistic picture is that the tutor has only an approximate appraisal of the cognitive states of students and that they formulate responses that do not require fine-tuning of the student model (Chi et al., 2004; Graesser et al., 1995).

Another dimension of student modeling consists of student emotions and motivation. Indeed, connections between complex learning and emotions have received increasing attention in the fields of psychology and education (Deci & Ryan, 2002; Dweck, 2002; Gee, 2003; Lepper & Henderlong, 2000; Linnenbrink & Pintrich, 2002; Meyer & Turner, 2006). Studies that have tracked the emotions during tutoring have identified the predominate emotions, namely confusion, frustration, boredom, anxiety, and flow/engagement, with delight and surprise occurring less frequently (Baker, D'Mello, Rodrigo, & Graesser, in press; Craig, Graesser, Sullins, & Gholson, 2004; D'Mello, Craig, Witherspoon, McDaniel, & Graesser, 2008; D'Mello, Graesser, & Picard, 2007). Aside from detecting these student emotions, it is important for tutors to adopt pedagogical and motivational strategies that are effectively coordinated with the students' emotions. For example, Lepper, Drake, and O'Donnell (1998) proposed an INSPIRE model to promote this integration. This model encourages the tutor to nurture the student by being empathetic and attentive to the student's needs, to assign tasks that are not too easy or difficult, to give indirect feedback on erroneous student contributions rather than harsh feedback, to encourage the student to work hard and face challenges, to empower the student with useful skills, and to pursue topics they are curious about.

Meyer and Turner (2006) identified three theories that are particularly relevant to understanding the links between emotions and learning: academic risk taking, flow, and goals (Meyer & Turner, 2006). The academic risk theory contrasts (a) the adventuresome learners who want to be challenged with difficult tasks, take risks of failure, and manage negative emotions when they occur and (b) the cautious learners who tackle easier tasks, take fewer risks, and minimize failure and the resulting negative emotions (Clifford, 1991). According to flow theory (Csikszentmihaly, 1990), the learner is in a state of flow when the learner is so deeply engaged in learning the material that time and fatigue disappear. When students are in the flow state, they are at an optimal zone of facing challenges and conquering the challenges by applying their knowledge and skills. Goal theory emphasizes the role of goals in predicting and regulating emotions (Dweck, 2002). Outcomes that achieve challenging goals result in positive emotions whereas outcomes that jeopardize goal accomplishment result in negative emotions.

Available evidence indicates that human tutors are limited in their ability to conduct student modeling on the psychological states of learners, whether they be cognitive states or emotions (D'Mello & Graesser, in press; Graesser, D'Mello, & Person, 2009). Most human tutors also are not sufficiently trained to implement a wide range of promising pedagogical strategies that are known to help learning. This of course opens the door to pursue computer tutors that take the tutoring process to the next level. We now turn to the world of Intelligent Tutoring Systems (ITS).

Intelligent Tutoring Systems

Those who work in the ITS world are inspired by the notion that learning will improve by implementing powerful intelligent algorithms that adapt to the learner at a fine-grained level and

that instantiate complex principles of learning. In this chapter we assume that ITS environments are a generation beyond conventional computer-based training (CBT). Many CBT systems also adapt to individual learners, but they do so at a more course-grain level with simple learning principles. In a prototypical CBT system, the learner (a) studies material presented in a lesson, (b) gets tested with a multiple choice test or another objective test, (c) gets feedback on the test performance, (d) re-studies the material if the performance in c is below threshold, and (e) progresses to a new topic if performance exceeds threshold. The order of topics presented and tested typically follows a predetermined order, such as ordering on complexity (simple to complex) or g ordering on prerequisites (Gagné, 1985). The materials presented in a lesson can vary in CBT, including organized text with figures, tables, and diagrams (essentially books on the web), multimedia, problems to solve, example problems with solutions worked out, and other classes of learning objects. CBT has been investigated extensively for decades and has an associated mature technology. Meta-analyses show effect sizes of 0.39 sigma compared to classrooms (Dodds & Fletcher, 2004), whereas Mayer's (2009) analyses of multimedia have substantially higher sigma. The amount of time that learners spend studying the material in CBT has a 0.35 correlation with learning performance (Taraban, Rynearson, & Stalcup, 2001) and can be optimized by contingencies that distribute practice (Pashler et al., 2007).

These CBT systems are an important class of learning environments that can serve as tutors. However, the next generation of ITS went a giant step further that enhanced the adaptability, grain-size, and power of computerized learning environments. The processes of tracking knowledge (called user modeling) and adaptively responding to the learner incorporate computational models in artificial intelligence and cognitive science, such as production systems, case-based reasoning, Bayes networks, theorem proving, and constraint satisfaction algorithms.

These models will be elaborated later in this chapter. It is beyond the scope of this chapter to sharply divide systems that are CBTs versus ITS (Doignon & Falmagne, 1999; O'Neil & Perez, 2003), but one dimension that is useful is the space of possible interactions that can be achieved with the two classes of systems. For ITS, every tutorial interaction is unique and the space of possible interactions is infinite. An ITS attempts to fill in very specific learning deficits, to correct very specific misconceptions, and implement dynamic sequencing and navigation. For CBT, interaction histories can be identical for multiple students and the interaction space is finite, if not small. Nevertheless, the distinction between CBT and ITS is not of central concern to this chapter other than to say that the distinction is blurry and that both classes of learning environments appear intelligent to the learners.

Successful systems have been developed for mathematically well-formed topics, including algebra, geometry, programming languages (the *Cognitive Tutors*: Anderson et al., 1995; Koedinger et al., 1997; Ritter et al., 2007, *ALEKS*: Doignon & Falmagne, 1999), physics (*Andes*, *Atlas*, and *Why/Atlas*: VanLehn et al., 2002; VanLehn et al., 2007), electronics (*SHERLOCK*: Lesgold, Lajoie, Bunzo, & Eggan, 1992), and information technology (*KERMIT*: Mitrovic, Martin, & Suraweera, , 2007). These systems show impressive learning gains (1.00 sigma, approximately, Corbett, 2001; Dodds & Fletcher, 2004) compared with suitable control conditions, particularly for deeper levels of comprehension. School systems are adopting ITS at an increasing pace even though they are initially expensive to build.

Recent ITS environments handle knowledge domains that have a stronger verbal foundation as opposed to mathematics and precise analytical reasoning. The *Intelligent Essay Assessor* (Landauer, Laham, & Foltz, 2000; Landauer, 2007) and *e-Rater* (Burstein, 2003) grade essays on science, history, and other topics as reliably as experts of English composition.

AutoTutor (Graesser, Chipman, Haynes, & Olney, 2005; Graesser, Jeon, & Dufty, 2008; Graesser, Lu et al., 2004) helps college students learn about computer literacy, physics, and critical thinking skills by holding conversations in natural language. AutoTutor shows learning gains of approximately 0.80 sigma compared with reading a textbook for an equivalent amount of time (Graesser, Lu et al., 2004; VanLehn et al., 2007). These systems automatically analyze language and discourse by incorporating recent advances in computational linguistics (Jurafsky & Martin, 2008) and information retrieval, notably latent semantic analysis (Landauer, McNamara, Dennis, & Kintsch, 2007; Millis et al., 2004).

At this point we turn to some recent ITS environments that have been tested on thousands of students and have proven effective in helping students learn. These systems also have scientific principles of learning that guide their design. The systems include the cognitive tutors, constraint-based tutors, case-based tutors, and tutors with animated conversational agents. Most of the systems fit within VanLehn's (2006) analyses of outer loop and inner loop when characterizing the scaffolding of solutions to problems, answers to questions, or completion of complex tasks in an ITS. The outer loop involves the selection of problems, the judgment of mastery of a problem, and other more global aspects of the tutorial interaction. The inner loop consists of covering individual steps within a problem at a more micro-level. Adaptivity and intelligence are necessary at both the outer loop and the inner loop in a bona fide ITS.

Cognitive Tutor

One of the salient success stories of transferring science to useful technology is captured in the Cognitive Tutor, a class of tutoring systems built by researchers at Carnegie Mellon University and produced by Carnegie Learning, Inc. The Cognitive Tutor is built on careful research grounded in cognitive theory and extensive real-world trials, and has realized the

ultimate goal of improvements over the status quo of classroom teaching. Its widespread implementation has drawn interest to both its inner psychological mechanisms and to its efficacy.

The Cognitive Tutor instruction is based on a cognitive model developed by Anderson (1990), called adaptive control of thought (ACT, or ACT-R in its updated form). The Cognitive Tutor has a curriculum of problems, with each problem having anticipated correct information (called *expectations*) and anticipated *misconceptions*. The software can adaptively identify a student's problem solving strategy through their actions and comparisons with the expectations and misconceptions. This comparison process is called *model tracing*. More specifically, the system constantly compares the student's actions to correct and incorrect potential actions that are represented in the cognitive model. Through these pattern matching comparison operations, the system can detect the many of the misconceptions that underlie the student's activities. The system is able to trace the student's progress using these comparisons and to give feedback when it is appropriate. When the system has decided that enough of the skill requirements have been met for mastery, the tutor and student move on to a new section.

The Cognitive Tutor makes use of two kinds of knowledge, called *declarative knowledge* and *procedural knowledge*, to represent the skills the student must acquire in learning to solve a problem. Declarative knowledge is primarily concerned with static factual information that can readily be expressed in language. In contrast, procedural knowledge handles how to do things. Though procedural knowledge is often limited to a specific context, it is also more deeply ingrained in a student's knowledge structure and often acted upon more quickly. Conversely, declarative knowledge can be slower and more deliberate (particularly if it is not well-learned), but it applies to a broader range of situations than does procedural knowledge (Ritter et al., 2007).

Any common math problem consists of a combination of declarative and procedural knowledge. For example, consider a student trying to solve the problem below.

$$\begin{array}{r} 336 \\ +848 \\ \hline 4 \end{array}$$

The student would have to have the declarative knowledge component “ $6 + 8 = 14$ ” stored in memory in addition to making sure that the production rules are in place to retrieve this fact.

Production rules are contextualized procedural knowledge that shape the core of the Cognitive Tutor. Production rules help determine the manner in which student behavior is interpreted and also the knowledge students should gain as part of the learning process. In our example problem adopted from Anderson and Gluck (2001), one of the relevant production rules would be:

IF the goal is to add n_1 and n_2 in a column
& $n_1 + n_2 = n_3$
THEN set as a subgoal to write n_3 in that column.

According to ACT-R, an important part of cognition is simply a large set of production rules that accumulate in long-term memory, that get activated by the contents of working memory, and that are dynamically composed in sequence when a particular problem is solved. An important part of learning is accessing and mastering these production rules in addition to the declarative knowledge. Behaviors performed by the student reflect the production rules and declarative knowledge, so the system can reconstruct what knowledge the student has already mastered versus has yet to learn (Anderson & Gluck, 2001). Using this student model, ACT-R can target those knowledge components that are missing in a student’s education and can select problems that specifically address those components. If successful, this would of course be a giant step forward beyond normal human tutoring.

Cognitive Tutor has a large number of skills for the student to learn. In four of their curricula (Bridge to Algebra, Algebra 1, Geometry or Algebra 2), there are 2,400 skills (or

collection of knowledge components) for the student to learn (Ritter et al., 2009). This is a very large space of detailed content, far beyond school standards, the knowledge of human teachers, and conventional CBT. The goal of Cognitive Tutor is to scaffold the correct methods for solving problems with the student until they become automatized after multiple problems in multiple contexts. This is accomplished by breaking down knowledge into smaller components, which can then be resurrected in particular problems in order to strengthen the student's knowledge into something well specified and procedural. Since any given task is made up of a combination of procedural and declarative knowledge components, the ultimate goal is to proceduralize the retrieval of this declarative knowledge in order to speed up and strengthen its availability, thereby making the right facts and procedures highly accessible during problem solving (Ritter et al., 2007). Additionally, a series of well-learned knowledge components can be put together to solve larger, more complex tasks (Lee & Anderson, 2001).

Cognitive Tutor also offers helps and hints, which are intended to aid the student in problem solving. Students can see their progress in Cognitive Tutor by looking at their *skillmeter*, which logs how many skills the student has acquired and depicts them in progress bars. The system gives just-in-time feedback when the student commits an error (Ritter et al., 2007). Cognitive Tutor includes a mechanism where the student can solicit hints to overcome an impasse. More specifically, there are three levels of hints. The first level may simply remind the student of the goal, whereas the second level offers more specific help, and the third level comes close to directly offering the student the answer for a particular step in the problem solving. An example of an intermediate hint would be "As you can see in the diagram, Angles 1 and 2 are adjacent angles. How does this information help to find the measure of Angle 2?" when the student is learning about angles (Roll et al., 2006). These hints can be highly effective when used

properly. However, some students attempt to “game the system,” or abuse the hint function to quickly get through a lesson (Alevan, McLaren, Roll, & Koedinger, 2006; Baker, Corbett, Koedinger, & Wagner, 2004). Gaming the system has been associated with lower learning outcomes for students and may be a consequence of learned helplessness.

As discussed earlier in this chapter, Cognitive Tutor is a widely used ITS and produces impressive learning gains in both experimental and classroom settings. Corbett (2001) tested various components of a cognitive tutor that teaches computer programming, looking for those aspects of the system that produce the most learning. Modeling tracing, when compared with no model tracing, had an effect size of 0.75 sigma. When students were exposed to a model tracing system that encourages mastery of skills, Corbett found a 0.89 sigma over simple model tracing. Significant effect sizes have also been found in their investigations into Cognitive Tutor in the school system. Their first classroom studies in Pittsburgh showed that Cognitive Tutor students excelled with an average of 0.6 sigma when compared to students in a traditional Algebra class. According to Ritter et al. (2007), standardized tests show overall effect sizes of 0.3 sigma and the *What Works Clearinghouse* investigations show an effect size of 0.4 sigma.

To be accurate, however, the results of the Cognitive Tutor are not uniformly rosy. For example, the representations and problems in which Cognitive Tutor students showed extremely high gains over traditional algebra students were experimenter-designed (Koedinger et al., 1997). A large-scale study in Miami with over 6,000 students showed that Cognitive Tutor students scored 0.22 sigma over their traditional Algebra student counterparts, but only scored 0.02 sigma better than the traditional students on the statewide standardized test (Shneyderman, 2001). It is widely acknowledged that there are challenges in scaling up any intervention and that the results

will invariably be mixed. Cognitive Tutor will continue to be modified in the future in an attempt to optimize learning gains in a wide range of contexts and populations.

Constraint-Based Tutors

Constraint-based modeling (CBM) is an approach first proposed by Ohlsson (Ohlsson, 1994, 1992) and later extended by Ohlsson and Mitrovic (2007). The core idea of CBM is to model the declarative structure of a good solution rather than the procedural steps leading to a good solution. Thus, CBM contrasts heavily with the model-tracing approach to student modeling which models each step of an expert solution, perhaps ignoring alternate solutions. CBM instead has much conceptual similarity with declarative styles of programming, like Prolog (Bratko, 1986), which define relationships between entities rather than operations on entities. This abstraction thus focuses on what properties a good solution must have rather than how it is obtained.

Ohlsson (1994) gives a concrete example of constraint-based modeling in the domain of subtraction. Subtraction has two core concepts, each giving rise to a constraint. The first core concept is place value, meaning that the position of the digit affects its quantity, e.g. 9 in the tens place represents the quantity 90. The second core concept of subtraction is regrouping, in which the digits expressing a quantity may change without changing the value of the quantity, e.g. $90 = 9*10 + 0*1 = 80*10 + 10*1$, so long as the decrement in one digit is offset by an increment in the other. The two constraints that follow from these core concepts are:

Constraint 1: Increments and corresponding decrements must occur together (otherwise the value of the numeral has changed)

Constraint 2: An increment of ten should not occur unless the digit in the position to the left is decremented by one.

The key observation is that a correct solution can never violate either of these constraints, no matter what order of operations is followed. Thus, the style of constraints is declarative rather than procedural.

In CBM, the declarative structure of a good solution is composed of a set of state constraints (Ohlsson, 1994). Each constraint is composed of a relevance condition (R) and a satisfaction condition (S). The relevance condition specifies when the constraint is relevant. Only in these conditions is the state constraint meaningful. The satisfaction condition specifies whether the state constraint has been violated. A relevant, satisfied state constraint corresponds to an aspect of the solution that is correct. A relevant, unsatisfied state constraint indicates a flaw in the solution.

There are two proposed advantages to CBM over traditional student models like model-tracing and buggy libraries (Ohlsson, 1994). First, CBM is able to account for a wider array of student behavior, i.e. greater deviations from the correct solution path, than either of these methods. This advantage stems from the basic property of CBM that solution paths aren't modeled. The second major advantage of CBM is that it is substantially less effort-intensive to create student models using CBM than traditional methods. Both of these claimed advantages have been explored in the literature, leading to a more elaborate and nuanced understanding of the tradeoffs between CBM and other modeling approaches.

Several CBM tutoring systems have been built by Mitrovic and colleagues with encouraging results (Mitrovic, Martin, & Suraweera, 2007; Mitrovic & Ohlsson, 1999; Mitrovic, Martin, & Mayo, 2002; Suraweera & Mitrovic, 2004). Particularly noteworthy are those that support learning of database and *SQL* (Structured Query Language) design. These systems have been incorporated into Addison-Wesley's *Database Place*, accessible by anyone who has bought

a database textbook from Addison-Wesley (Mitrovic, Martin, & Suraweera, 2007). *KERMIT* (Suraweera & Mitrovic, 2004) is an entity-relationship tutor that focuses on database design. In a two hour pretest-posttest study with randomized assignment, students using *KERMIT* had significantly higher learning gains than students from the same class who used *KERMIT* with disabled constraint-based feedback, with an effect size of 0.63.

It is informative to compare CBM with the model-tracing architecture of the Cognitive Tutors. This has been one of the fundamental debates in the ITS literature in recent years. Table 1 contrasts properties of the two models according to Mitrovic, Koedinger, and Martin (2003). For example, it appears that CBM is less effortful to build, but less capable of giving specific advice to the learner, whereas model-tracing is the opposite: more effortful to build but more capable of giving specific advice (Mitrovic et al., 2003). Kodaganallur, Weitz, and Rosenthal (2006) conducted a more thorough investigation of two complete systems in the domain of hypothesis testing. When compared with model-tracing, CBM accounted for a narrower array of student behavior, required libraries to handle student misconceptions and errors, was unable to give procedural remediation, was incapable of giving fine-grained feedback, and was likely to give incorrect feedback to proper solutions. However, a number of methodological problems with this analysis were noted by Mitrovic and Ohlsson (2007). It suffices to say that the debate continues on the relative strengths and liabilities of these two architectures, but it is beyond the scope of this chapter to elaborate and resolve the controversy.

Table 1

Comparative analysis of CBM and MT (Mitrovic, Koedinger, & Martin, 2003)

Property	Model Tracing	Constraint-Based Modeling
Knowledge representation	Production rules (procedural)	Constraints (declarative)
Cognitive fidelity	Tends to be higher	Tends to be lower
What is evaluated	Action	Problem state
Problem solving strategy	Implemented ones	Flexible to any strategy
Solutions	Tend to be computed, but can be stored	One correct solution stored, but can be computed
Feedback	Tends to be immediate, but can be delayed	Tends to be delayed, but can be immediate
Problem-solving hints	Yes	Only on missing elements, but not strategy
Problem solved	'Done' productions	No violated constraints
Diagnosis if no match	Solution is incorrect	Solution is correct
Bugs represented	Yes	No
Implementation effort	Tends to be harder, but can be made easier with loss of other advantages	Tends to be easier, but can be made harder to gain other advantages

Case-Based Reasoning

ITS with Case-based reasoning (CBR) are inspired by cognitive theories in psychology, education, and computer science that emphasize the importance of specific cases, exemplars, or scenarios in constraining and guiding our reasoning (Leake, 1996; Ross, 1987; Schank, 1999).

There are two basic premises in CBR that are differentially emphasized in the literature. The first basic premise is that memory is organized by cases consisting of a problem description, its solution, and associated outcomes (Watson & Marir, 1994). Accordingly, problem solving makes use of previously encountered cases rather than by proceeding from first principles. Although there is wide variation in the field as to the adaptation and use of cases, implemented systems generally follow four steps (Aamodt & Plaza, 1994):

RETRIEVE the most similar case(s); (indexing problem)

REUSE the case(s) to attempt to solve the problem; (adaptation problem)

REVISE the proposed solution if necessary, and

RETAIN the new solution as a part of a new case.

The second basic premise of CBR is that memory is dynamically organized around cases (Schank, 1999), meaning that the outcome of the four steps above can not only cause cases to be re-indexed using an existing scheme but can also drive the indexing scheme itself to change. Therefore learning in the CBR paradigm goes beyond adding new cases after successful REUSE and beyond adding new cases after failed REUSE and successful REVISION. Even though success and failure can drive the creation of new cases, they can also drive the way all existing cases are organized and thus their future use (Leake, 1996).

Like ACT-R, CBR has been used as an underlying theory for the development of learning environments (Kolodner et al., 2003; Kolodner, Cox, & Gonzalez-Calero, 2005; Schank, Fano, Bell, & Jona, 1994). As a theory of learning, CBR implies that human learners engage in case-based analogical reasoning as they solve problems and learn by solving the problems. One might expect CBR learning environments to proceed in a similar fashion to model-tracing and CBM tutors: implement a tutor capable of solving the problem, allow the student to solve the problem, and then provide feedback based on the differences between the student's solution and the tutors. However, perhaps because of the complications involved with implementing a model-based reasoner on top of a CBR system, an ITS analogous to model-tracing and constraint-based modeling has yet to be implemented. Instead, CBR learning environments give learners the resources to implement CBR on their own. That is, designers of these CBR systems present

learners with activities designed to promote CBR activities: identifying problems, retrieving cases, adapting solutions, predicting outcomes, evaluating outcomes, and updating a case library.

There are two CBR paradigms that proceed in this fashion of facilitating design by human learners. The first is exemplified by two environments called *Goal-Based Scenarios* (Schank, Fano, Bell, & Jona, 1994) and *Learning by Design* (Kolodner, Cox, & Gonzalez-Calero, 2005), both of which are highly integrated with classroom activities. Goal-Based Scenarios use simulated worlds as a context for learning (Schank et al., 1994). For example *Broadcast News*, puts students in the scenario of having to create their own news program. Cases are news sources from the previous day, and these are RETRIEVED via tasks students perform to establish the social issues in each story. Experts are available to answer questions and provide feedback, thereby helping the students complete the REUSE and REVISE phases.

In contrast, *Learning by Design* frames the learning task as a design task (Kolodner et al., 2003). An example of this is designing a parachute. The *Learning by Design* addresses this task in 6 phases, with learning occurring in groups: clarifying the question, making a hypothesis, designing an investigation (using existing cases as input, REUSE), conducting the investigation (REUSE), analyzing results (REVISE), and group presentation. Kolodner et al. (2005) review educational outcomes in this paradigm and draw two conclusions. The first is that the reviewed CBR classes have significantly larger simple learning gains (posttest – pretest) compared to control classrooms, although effect sizes have not been reported. The second conclusion is that CBR classes have greater skill in collaborating and in scientific reasoning than matched peers. However, more rigorous tests of these claims await future research.

The second CBR paradigm involves support from a computer environment for one-on-one learning. Perhaps the best known work of this type is the law-based learning environment by

Aleven and colleagues (Aleven, 2003; Ashley & Brüningshaus, 2009). The most current system, CATO, is a CBR system for legal argumentation, i.e. the arguments attorneys make using past legal cases. CATO uses its case library and domain background knowledge to organize multi-case arguments, reason about significant differences between cases, and determine which cases are most relevant to the current situation. Students using CATO practice two types of tasks, theory-testing and legal argumentation, both of which rely heavily on CATO's case library. Theory-testing requires the student to predict a ruling on a hypothetical case by first forming a hypothesis, retrieving relevant cases from CATO (RETRIEVE), and then evaluating their hypothesis in light of the retrieved cases (REUSE, REVISE). Legal argumentation requires the student to write legal arguments for both the defendant and plaintiff on a hypothetical case. Students first study the hypothetical case and then retrieve relevant cases from CATO (RETRIEVE). Next the students study example arguments that CATO generates dynamically based on the selected cases, in a kind of multi-case REUSE/REVISE. Students iteratively use this dynamic generation capability to explore the outcomes of combining different sets of cases, successively refining their arguments until they are complete (RETRIEVE/REUSE/REVISE). For argumentation, learning with CATO was not significantly different than learning from a human instructor when matched for time and content, in both cases in a law school setting (Aleven, 2003).

Conversational Agents

Animated conversational agents play a central role in some of the recent advanced learning environments (Atkinson, 2002; Baylor & Kim, 2005; Gholson et al., 2009; Graesser, Chipman, Haynes, & Olney, 2005; Johnson, Rickel, & Lester, 2000; McNamara, Levinstein, & Boonthum, 2004; Moreno & Mayer, 2007; Reeves & Nass, 1996). These agents interact with students and

help them learn by either modelling good pedagogy or by holding a conversation. The agents may take on different roles: mentors, tutors, peers, players in multiparty games, or avatars in the virtual worlds. The students communicate with the agents through speech, keyboard, gesture, touch panel screen, or conventional input channels. In turn, the agents express themselves with speech, facial expression, gesture, posture, and other embodied actions. Intelligent agents with speech recognition essentially hold a face-to-face, mixed-initiative dialogue with the student, just as humans do (Cole et al., 2003; Graesser, Jackson, & McDaniel, 2007; Gratch et al., 2002; Johnson & Beal, 2005).

Single agents model individuals with different knowledge, personalities, physical features, and styles. Ensembles of agents model social interaction. These systems are major milestones that could only be achieved by advances in discourse processing, computational linguistics, learning sciences and other fields.

AutoTutor is an intelligent tutoring system that helps students learn through tutorial dialogue in language (Graesser, Dufty, & Jeon, 2008; Graesser, Hu, & McNamara, 2005; Graesser et al., 2005). AutoTutor's dialogues are organized around difficult questions and problems that require reasoning and explanations in the answers. For example, below are two example challenging questions from two of the subject matters that get tutored: Newtonian physics and computer literacy.

PHYSICS QUESTION: If a lightweight car and a massive truck have a head-on collision, upon which vehicle is the impact force greater? Which vehicle undergoes the greater change in its motion, and why?

COMPUTER LITERACY QUESTION: When you turn on the computer, how is the operating system first activated and loaded into RAM?

These questions require the learner to construct approximately 3-7 sentences in an ideal answer and to exhibit reasoning in natural language. These are hardly the fill-in-the-blank questions or multiple-choice questions that many associate with learning technologies on computers. It takes a conversation to answer each one of these challenging questions. The dialogue for one of these challenging questions typically requires 50-100 conversational turns between AutoTutor and the student.

The structure of the dialogue in both AutoTutor attempts to simulate that of human tutors, as was discussed earlier. More specifically, AutoTutor implements the three conversational structures: (a) a 5-step dialogue frame, (b) expectation and misconception-tailored dialogue, and (c) conversational turn management. These three levels can be automated and produce respectable tutorial dialogue. AutoTutor can keep the dialogue on track because it is always comparing what the student says to anticipated input (i.e., the expectations and misconceptions in the curriculum script). Pattern matching operations and pattern completion mechanisms drive the comparison. These matching and completion operations are based on latent semantic analysis (Landauer et al., 2007) and symbolic interpretation algorithms (Rus & Graesser, 2006) that are beyond the scope of this article to address. AutoTutor cannot interpret student contributions that have no matches to content in the curriculum script. This of course limits true mixed-initiative dialogue. That is, AutoTutor cannot explore the topic changes and tangents of students as the students introduce them. However, as we discussed in the previous section on human tutoring, (a) human tutors rarely tolerate true mixed-initiative dialogue with students changing topics that steer the conversation off course and (b) most students rarely change topics, rarely ask questions, and rarely take the initiative to grab the conversational floor. Instead, it is the tutor that takes the lead and drives the dialogue. AutoTutor and human tutors are very similar in these respects.

The learning gains of AutoTutor have been evaluated in over 20 experiments conducted during the last 12 years. 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's learning gains have varied between 0 and 2.1 sigma (a mean of 0.8), depending on the learning performance measure, the comparison condition, the subject matter, and the version of AutoTutor. Approximately a dozen measures of learning have been collected in these assessments on the topics of computer literacy and physics, including: (a) multiple choice questions on shallow knowledge that tap definitions, facts and properties of concepts, (b) multiple choice questions on deep knowledge that taps causal reasoning, justifications of claims, and functional underpinnings of procedures, (c) essay quality when students attempt to answer challenging problems, (d) a cloze task that has subjects fill in missing words of texts that articulate explanatory reasoning on the subject matter, and (e) performance on problems that require problem solving. AutoTutor is most impressive for the multiple choice questions that tap deep reasoning.

The agents described above interact with students one-to-one. Learning environments can also have pairs of agents interact with the student as a triologue and larger ensembles of agents that exhibit ideal learning strategies and social interactions. It is extraordinarily difficult to train teachers and tutors to apply specific pedagogical techniques, especially when the techniques clash with the pragmatic constraints and habits of everyday conversation. However, pedagogical agents can be designed to have such precise forms of interaction.

As an example, *iSTART (Interactive Strategy Trainer for Active Reading and Thinking)* is an automated strategy trainer that helps students become better readers by constructing self-explanations of the text (McNamara et al., 2004). The construction of self-explanations during

reading is known to facilitate deep comprehension (Chi et al., 1994; Pressley & Afflerbach, 1995), especially when there is some context-sensitive feedback on the explanations that get produced (Palincsar & Brown, 1984). The iSTART interventions teach readers to self-explain using five reading strategies: *monitoring comprehension* (i.e., recognizing comprehension failures and the need for remedial strategies), *paraphrasing* explicit text, making *bridging inferences* between the current sentence and prior text, making *predictions* about the subsequent text, and *elaborating* the text with links to what the reader already knows. Groups of animated conversational agents scaffold these strategies in three phases of training. In an *Introduction Module*, a trio of animated agents (an instructor and two students) collaboratively describe self-explanation strategies with each other. In a *Demonstration Module*, two Microsoft Agent characters (Merlin and Genie) demonstrate the use of self-explanation in the context of a science passage and the trainee identifies the strategies being used. In a final *Practice* phase, Merlin coaches and provides feedback to the trainee one-to-one while the trainee practices self-explanation reading strategies. For each sentence in a text, Merlin reads the sentence and asks the trainee to self-explain it by typing a self-explanation. Merlin gives feedback and asks the trainee to modify unsatisfactory self-explanations.

Studies have evaluated the impact of iSTART on both reading strategies and comprehension for thousands of students in K12 and college (McNamara, Best, O'Reilly, & Ozuru, 2006). The three-phase iSTART training (approximately 3 hours) has been compared with a control condition that didactically trains students on self-explanation, but without any vicariously modeling and any feedback via the agents. After training, the participants are asked to self-explain a transfer text (e.g., on heart disease) and are subsequently given comprehension

tests. The results have revealed that strategies and comprehension are facilitated by iSTART, with impressive effect sizes (.04 to 1.4 sigma) for strategy use and for comprehension.

Future Directions

This chapter has made the case that tutoring by humans and computers is a powerful learning environment to the extent that it implements sensible principles of learning. However, there are still a large number of unanswered fundamental questions that need attention in future research. This section identifies some directions for further inquiry from the standpoint of ITS environments.

Computer tutors allow more control over the tutoring process than human tutors can provide. This opens up the possibility of new programs of research that systematically compare different versions of an ITS and different types of ITS. All ITS have multiple modules, such as the knowledge base, the student's ability and mastery profile, decision rules that select problems, scaffolding strategies, help systems, feedback, media on the human-computer interface, and so on. Which of these components are responsible for any learning gains of the ITS? It is possible to systematically manipulate the quality or presence of each component in *lesion* studies that manipulate the presence or absence of different tutoring components. The number of conditions in manipulation studies of course grows with the number of components. If there are 6 major components, with each level varying in 2 levels of quality, then there would be $2^6 = 64$ conditions in a factorial design. That would require nearly 2000 students in a between-subjects design with 30 students randomly assigned to each of the 64 conditions. If a variable has an impact on learning in a curvilinear fashion, then we would need three levels, resulting in $3^6 = 729$ conditions and nearly 22,000 students. This of course seems impractical, although thousands of

students receive training on some ITS environments on the web (Heffernan, Koedinger, & Razzaq, 2008). The alternative would be to selectively focus on one or two modules at a time.

Comparisons need to be made between different computer tutors that handle the same subject matter. Algebra, for example, can be trained with the Cognitive Tutors, ALEKS, Constraint-based Models, and perhaps even Case-based learning environments. Which of these provides the most effective learning for different populations of learners? It may be that there are aptitude-treatment interactions and, therefore, no clear winner. Eventually we would sort out which tutoring architecture works best for each population of learners.

The subject matters with verbal reasoning, as opposed to mathematical computation, need a different ITS architecture. The conversational agents are expected to play an important role in these topics that require verbal reasoning. Questions remain on how effective the conversational agents are compared to the more conventional graphical user interfaces. Is it best to make the interface resemble a face-to-face conversation with a human? Or does such anthropomorphic realism present a distraction from the subject matter? If the animated agent does resemble a human, what is the ideal personality of the agent and to what extent should it appear intelligent? Should a computer agent claim it understands the student, has empathy, and recognizes the student is frustrated? Or should it not pretend to have such human elements? What are the pragmatic ground rules of a computer agent who wants to bond with a human learner? These questions are currently unanswered.

One of the provocative tests in the future will pit human versus machine as tutors. Most people place their bets on the human tutors under the assumption that they will be more sensitive to the student's profile and be more creatively adaptive in guiding the student. However, the detailed analyses of human tutoring challenge such assumptions in light of the many illusions

that humans have about communication and the modest pedagogical strategies in their repertoire. Computers may do a better job in cracking the illusions of communication, in inducing student knowledge states, and in implementing complex intelligent tutoring strategies. A plausible case could easily be made for betting on the computer over the human tutor. Perhaps the ideal computer tutor emulates humans in some ways and complex non-human computations in other ways. Comparisons between human and computer tutors need to be made in a manner that equilibrates the conditions on content, time on task, and other extraneous variables that are secondary to pedagogy. As data roll in from these needed empirical studies, we make only one prediction with any semblance of confidence: There will be unpredictable and counterintuitive discoveries.

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