19. INTELLIGENT TUTORING SYSTEMS: PAST, PRESENT, AND FUTURE

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19.1 INTRODUCTION

Many aspects of intelligent tutoring systems (ITS) are addressed in a search for answers to the following main questions: (a) What are the precursors of ITS? (b) What does the term mean? (c) What are some important milestones and issues across the 25+ years of ITS history? (d) What is the status of ITS evaluations? (e) What is the future of ITS? Let’s start with an historical perspective.

19.2 PRECURSORS OF ITS

19.2.1 Early Mechanical Systems

Charles Babbage (early 1800s) is typically credited with being the first to envision a multipurpose computer. He dreamed of creating an all-purpose machine, which he called the analytic engine. However, because of the technological constraints of the time, he was never able to build his dream, although his ideas were developed by his descendants, as well as by others. In 1900, following the way of early (artificially) intelligent mechanical precedent, a new machine was invented: the early electronic computer. By the late 1930s, computer scientists were developing the first digital computers, which were large, extremely expensive, and used for solving problems in a wide variety of fields, including physics, mathematics, and engineering.

19.2.2 Programmed Instruction and Computer-Assisted Instruction

In the early 1940s, programmed instruction (PI) was educationally fashionable (see 23.4.2.1). This form of instruction was designed to help students learn specific skills and knowledge. It was typically presented in the form of a series of questions and answers, with the student progressing through the material at their own pace. PI was often used in schools, colleges, and universities as a way to deliver instruction in a structured and systematic manner.

In general, PI refers to any instructional methodology that utilizes a systematic approach to problem decomposition and teaching (e.g., Piaget, Cyert, Gagné & Watanabe). In some cases, PI (e.g., 1967, 1965, 1964; see 23.4.2.1) has been embedded in a computer program, known as computer-assisted instruction (CAI or computer-based training, CBT). Some similarities between PI and CAI are that both have well-defined curricula and branching routines (recursion being a prominent feature), which allows appropriate corrective action to be taken (Crowder, 1959). In other words, at every point in the curriculum, the computer program evaluates whether the student's answer is right or wrong and then moves the student to the proper path. Built-in remediation loops allow students who are attempting to answer a question incorrectly to obtain additional instruction. If learners answer correctly, they are moved ahead in the curriculum. Figure 19-1 illustrates a typical flow of events in CAI.

The teacher constructs all branching in the program, ahead of time. The normal PI procedure presents some material to be learned, followed by a problem to be solved that represents a subset of the curriculum's material. Problem solutions reveal the learner's acquisition of the knowledge or skill being taught or tested at that time. The student's answer is compared to the correct answer, then the computer gives appropriate feedback if the answer is correct, a new problem is selected and presented. If the student answers incorrectly, the computer diagnoses the problem, identifies the error, and provides feedback to the student. The process is repeated until the student answers correctly. The student's progress is tracked, and the computer provides appropriate feedback at each step. The student receives immediate feedback, which allows for immediate correction of errors, and provides opportunities for reinforcement and praise. The system adapts to each student's learning style and pace, providing individualized instruction to meet each student's needs.

As can be seen in Figure 19-1, there are several places where the simple model may be expanded to create more flexibility and, hence, student adaptability to individual differences. For instance, various mastery criteria can be imposed, where adequate scores have to be achieved before progressing to the next step. Therefore, the model may be adapted to different instructional settings, such as classroom, laboratory, or online learning environments. The system can be used for both instruction and assessment, allowing for a comprehensive approach to learning. The student's progress is tracked, and the computer provides appropriate feedback at each step. The system adapts to each student's learning style and pace, providing individualized instruction to meet each student's needs.

19.2.3 Intelligent Computer-Assisted Instruction

To distinguish between simple versus more adaptive PI, we refer to different terms such as CAI or computer-assisted instruction (CAI), computer-based instruction (CBI), and computer-assisted instruction (CAI). These terms are often interchangeably used in the literature, and the choice of terms may depend on the specific context or field of study. The main goal of computer-assisted instruction is to provide personalized instruction to each student, based on their individual needs and learning styles. This allows for a more effective and efficient learning experience, as students can receive tailored instruction that is specifically designed to meet their specific needs. This approach is particularly useful in settings where traditional classroom instruction may not be effective, such as in situations where students have different learning styles, or where there is a need to provide instruction to a large number of students with different abilities.
Suppose you wanted to build a computerized instructional system to help second-grade learners learn double-digit addition. If student A answered the following two problems: 22 + 30 = 62, and 46 + 37 = 83, you'd notice (with a fair amount of confidence) that A understood, and could successfully apply, the "carrying procedure." But consider some other responses. Student B answers the same problems with 51 and 73, student C answers with 61 and 205, and student D answers with 61 and 85. Simple CAl systems may be incapable of differentiating these incorrect solutions, and remediation would require all three students to redo the specific unit of instruction. But a big problem with this approach is that, typically, there is little difference between the remedial and original instruction. That means that a student who didn't get it right the first time may not get it right the second time if the same instruction and similar problems are used.

A more sensitive (or intelligent) response by the system would be to diagnose exactly B's errors as a failure to carry 1 to the next column, C's answer as the incorrect adding of the one column result (11 and 13) to the tens column, and D's as a probabilistic computational error in the second problem (mismatching 67 to 85 instead of 113). An intelligent system would remediate by specifically addressing each of the three qualitatively different errors.

19.2.1. Artificial Intelligence and Computerized Instruction. How can a computer system be programmed to perform intelligent? This question drives the empirical and engineering research in a field called artificial intelligence (AI). The simplest definition is that "AI is the study of mental faculties through the use of computational models." (Charniak & McDermott, 1985, p. 6). One of the main objectives of AI is to design and develop computer systems that can solve the same kinds of activities that we deem intelligent (e.g., solving a math problem like the one illustrated above), understanding natural language, programming a computer to perform some function(s), maneuvering an aircraft through obstacles, planning a wedding reception, and so forth, see also 22.4.1). There are far too many AI applications to delineate in this chapter. For our purposes, AI techniques relevant to ITS include those dealing with the simplified representation, storage, and retrieval of knowledge (e.g., a large collection of facts and skills—correct and buggy versions), as well as the effective communication of that information. All AI techniques can include inductive and deductive reasoning processes that allow a system to assess its own knowledge to derive novel (i.e., not programmed) answers to learners' questions.

Cognitive psychology also provides part of the answer to the question of how to get a computer to behave intelligently by examining issues related to the representation and organization of knowledge. Research in this area provides detailed specification for implementing intelligent computer programs. Cognitive psychology also addresses the issue of errors, a critical feature in the design of intelligent systems to avoid the creation of a system that is so complex as to be incomprehensible to the user. In traditional AI systems, error recovery and debugging are achieved through a combination of debugging tools and debugging techniques. The logical approach to error recovery is the one that is most widely used. In this approach, the system is designed to detect and report errors in the input, and to ask the user to correct the errors. The system then continues to execute the program, using the corrected input.
19. Intelligent Tutoring Systems: Past, Present, and Future

19.3 INTELLIGENT TUTORING SYSTEMS DEFINED

While many researchers in the field view ICAI and ITS as interchangeable designations, we make a subtle distinction between the two. ITS represents a more specific type of ICAI, due to the attributes discussed below.

19.3.1 Early Specifications of ITS

An early outline of ITS requirements was presented by Hartley and Steinman (1973). They argued that ITS must possess (a) knowledge of the domain (expert model), (b) knowledge of the learner (student model), and (c) knowledge of the learning strategy (meta-model).

19.3.2 ITS Components and Relationships

A student learns from ITS primarily by solving problems—ones that are appropriately selected or constructed. For example, when the student has already received some particular advice, and so on. After the feedback loop, the program updates the student's skills model (a record of the student's current knowledge and skills), and moves on to the next advice.

In summary, the standard approach to building a student model involves representing changing learner knowledge and skills. The computer responds to updated observations with a modified curriculum that is appropriately adjusted, instruction, and feedback, and is very much dependent on individual response histories. But an alternative approach involves assessing incoming knowledge and skills, either instead of, or in addition to, changing knowledge and skills. This alternative enables the student's model to adapt to both posterior and immediate performance information as well as their interaction (see Shute, 1995a, 1995b, 1995c). In fact, many have argued that incoming knowledge is the single most important determinant of subsequent learning (e.g., Alexander & Jolly, 1995; Dochy, 1995; Glass, 1984). Other kinds of systems may not even have a teachable process. For example, the strength of a student's (or teacher's) problem-solving skills is highly correlated with the student's (or teacher's) performance.
19.3.3 The "T" in ITS

Our working definition of computer-to-intelligence is that the system must behave intelligently, not actually be intelligent, like a human being. More specifically, we believe that an "intelligent" system must be able to (a) accurately diagnose students' knowledge structures, styles, and/or styles using principles, rather than programmed responses, to decide what to do next; and (b) adapt instruction according to the student's needs and progress. Moreover, the traditional intelligent tutoring system (ITS), takes a logical, rather than cross-contextual, perspective, focusing on the strengthening cognitive needs of a single learner at a time, rather than on stable individual differences (Ottoson, 1986, pp. 283-294).

In order to obtain a rough idea of the degree of consensus among researchers in the ITS community, 20 experts were asked to summarize, in a couple of sentences, their ideas on what the "T" in ITS means. Following are the different responses received (in alphabetical order, and slightly modified for readability).

Tang, J.: "Intelligent" in ITS stands for the ability to use (in a conversational way) different levels of abstraction, representation of the learner, the domain, and the instruction. The higher the range of abstraction, the higher the intelligence. The phrase "in a conversational way" implies that one should be able to go from specific (e.g., logical arguments) to abstract (e.g., learning characters, as well as the other way around, e.g., from general instructional strategies to specific instructional transactions).

Tobon, A.: An intelligent instruction system should observe what the student is doing during problem solving and modify it over a series of problem-solving sessions. Information from the system's interactions with the learner based on a dynamic assessment of the student's model of performance. Intelligent feedback means that the assessment of the learner is ongoing and feedback is appropriate to that particular learner in the context of where an impasse has been reached, and is not caused but generated on the spot, based on student needs.

Traynor, J.: "Intelligent" in ITS means that the system uses information about the student to perform a task. Further, it implies that this information is used to the assist the student's learning and to model the student's evolving knowledge.

Witt, W.: "Intelligent" in ITS tutoring systems, a milestone, is a process that involves the learner in a process by which the system requests new knowledge from the user. This new knowledge is then used to improve the system's understanding of the learner or the task. The system then uses this new knowledge to make decisions about what to do and how to adapt the instruction.

Wynn, D.: ITS is "intelligent" in that it has the ability to learn from experience, improve itself, and adapt to new situations. ITS is "intelligent" in that it can learn from experience, improve itself, and adapt to new situations. ITS is "intelligent" in that it can learn from experience, improve itself, and adapt to new situations.

Wixler, R.: ITS "Intelligent" means that it is able to observe the student's actions and deduce the student's knowledge. ITS "Intelligent" means that it is able to observe the student's actions and deduce the student's knowledge. ITS "Intelligent" means that it is able to observe the student's actions and deduce the student's knowledge. ITS "Intelligent" means that it is able to observe the student's actions and deduce the student's knowledge.
administered instruction developed before the 1970s was inflexible and didactic because the systems had very limited capabilities (i.e., memory capacity and computational speed) for adaptive diagnosis and feedback. Furthermore, "...the only theory available to guide instructional development was behavior therapy, which poorly matched the cognitive goals of education" (Langdell, 1998, p. 6; see 2.2). Over time, researchers in AI and cognitive psychology joined forces, and together provided a basis for a new generation of computer-based teaching programs. Some of the research issues that dominated the 70s are discussed below (see 5.2.3).

19.4.1.1 Real-Time Problem Generation. The earliest systems to incorporate some form of "classic" ITS elements were programs that generated problems and learning tasks, representing a big departure from the canned problems found in CAI databases (see also 7.5.2). For example, an LCT (1969) developed a computer-based learning system that created, in real time, small arithmetic problems and vocabulary recall tasks. A majority of this work was conducted in the area of form computer programs that generated problems that had been tailored to the knowledge and skill requirements of a particular student, thus providing the foundation for student modeling.

19.4.1.2 Simple Student Modeling. The Basic Instructional Program (BIP) developed procedural skills required in learning the programming language BASIC (Bart, Beard & Diamond, 1971). In BIP, all the student selected by solving problems based on what the student already knew (past performance), which skills to be taught next, and its analysis of the skills required (problems in the curriculum). Exercises were dynamically and individually selected per person (from a pool of 100 sample problems). Then teaching heuristics were applied to student model to identify skills to be taught, and exercises were selected that better involved those skills. Selection of appropriate exercises was based on information contained in a network called the Curriculum Information Network (CDI), relating tasks in the curriculum to issues in the domain knowledge. Thus, a teaching task in the tutor was represented in terms of its component skill requirements. Based on this analysis of BIP, Shute knew the component skills needed for solving a particular programming problem included such skills as initializing memory variables, use for negotiating with I. as final values, and so forth. Each task tapped a different set of skills.

19.4.1.3 Knowledge Representation. Classic CAI used pages of text to represent knowledge, but with little psychological validity. In contrast, Cardenelli's (1970) SCHOLAR program (often considered the first ITS) used a semantic net to represent domain knowledge (South American geography) as well as the student model. Nodes in the network had tags to indicate whether the concept was known to the student. This new application of semantic networks as a general means of knowledge representation supported student-teacher dialog with students. Not only could the computer ask questions of the student, but the student could also, theoretically, ask questions of the computer. One major limitation of this semantic knowledge representation was the difficulty of representing procedural knowledge (see 5.2).

19.4.1.4 Reactive Learning Environments. In reactive learning environments, the student responds to a learning environment in a variety of ways that extend understanding and help change the student's beliefs about the subject matter. The system could either ask questions of the student, or the student could initiate activities to elicit feedback. In computer-based educational software, this is referred to as student-driven learning. The designer's challenge is to design an environment that is interesting and motivating for the student.

19.4.1.5 Intelligent Tutoring Systems. The generation of ITSs from the 1970s to the 1980s was marked by the development of intelligent tutoring systems (ITSs), which were designed to provide personalized instruction to students. These systems were based on the principles of artificial intelligence (AI) and cognitive psychology, and they aimed to replicate the processes of human learning and reasoning. The main goal of ITSs was to provide a personalized learning experience, tailored to the individual student's needs and abilities. The design of ITSs involved the development of expert systems, which were used to represent the knowledge and skills required for a particular domain. These expert systems were then used to generate learning tasks and provide feedback to the student.

19.4.1.6 Multi-User Systems. As ITSs became more sophisticated, they began to incorporate features that allowed multiple students to interact with the same learning environment simultaneously. These multi-user ITSs were designed to support collaborative learning, where students could work together to solve problems, share knowledge, and support each other's learning. Multi-user ITSs were particularly useful in educational settings, where students might benefit from the social interactions that occur in a classroom setting.

19.4.1.7 Knowledge-Based Systems. Knowledge-based systems (KBSs) were another important development in the field of ITSs. These systems were designed to provide expert-level knowledge and guidance to users in specific domains. KBSs were based on a combination of AI techniques, including rule-based systems and case-based reasoning. They were particularly useful in domains where knowledge was difficult to formalize, such as medical diagnosis or legal advice. KBSs were used to provide personalized advice, diagnosis, or guidance to users, based on their specific needs and situations.

19.4.1.8 Expert Systems and Tutoring. Expert systems were another type of ITS that emerged in the 1980s. These systems were designed to provide expert-level knowledge and advice to users in specific domains. Expert systems were based on a combination of AI techniques, including rule-based systems and case-based reasoning. They were particularly useful in domains where knowledge was difficult to formalize, such as medical diagnosis or legal advice. Expert systems were used to provide personalized advice, diagnosis, or guidance to users, based on their specific needs and situations.

19.4.1.9 Intelligent Tutoring Systems. Intelligent tutoring systems (ITSs) are computer-based systems designed to provide personalized instruction to students. These systems are based on the principles of artificial intelligence (AI) and cognitive psychology, and they aim to replicate the processes of human learning and reasoning. The main goal of ITSs is to provide a personalized learning experience, tailored to the individual student's needs and abilities. ITSs are designed to provide feedback to the student, based on their answers to prompts or exercises, and to adapt the instruction to the student's level of understanding.

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19.5.1.3 Knowledge Representation. Knowledge representation is a crucial aspect of ITSs. The way knowledge is represented can significantly affect the effectiveness of the tutoring system. Knowledge representation involves identifying the components of knowledge, such as facts, rules, and procedures, and determining how to represent them in a way that is understandable and usable by the system. Common representations include semantic networks, production systems, and frame-based representations.

19.5.1.4 Expert Systems and Tutoring. Expert systems and tutoring systems are two types of ITSs that emerged in the 1980s. Expert systems are designed to provide expert-level knowledge and advice to users in specific domains. Tutoring systems are designed to provide personalized instruction to students. Both expert systems and tutoring systems are based on the principles of artificial intelligence (AI) and cognitive psychology, and they aim to replicate the processes of human learning and reasoning. The main goal of both systems is to provide a personalized learning experience, tailored to the individual student's needs and abilities. Expert systems and tutoring systems are designed to provide feedback to the student, based on their answers to prompts or exercises, and to adapt the instruction to the student's level of understanding.

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19.4.2. Model Tracing
Anderson and his colleagues at Carnegie-Mellon University developed a model-tracing approach to tutoring based on production systems as a way of modeling student behavior. The model-tracing approach has been employed in a variety of tutoring systems, such as the one developed by Anderson, Reiser, & Reiser (1985) and the geometry tutor (Anderson, Boyle, & Yot, 1983). Model tracing provides a powerful way both to validate cognitive theories (e.g., Anderson, 1983) and to deliver low-level personalization. The approach works by identifying patterns of production rules that model the learners' "chunks" of cognitive skills. A learner's acquisition of these chunks is monitored (i.e., the student model is traced) and used to guide instruction (and generate hypothetical explanations for the learner's behavior). In this way, the model tracing approach can be used to develop adaptive tutorials and, in general, to improve educational software.

19.4.2.2. Model Tracing in Problem Solving
Problem solving is a complex process that involves the application of cognitive skills and strategies in order to achieve a specific goal. The model tracing approach can be used to develop adaptive problem-solving tutors that provide feedback and guidance to help learners improve their problem-solving skills. These tutors can be used in a wide range of domains, from mathematics and science to language and reading comprehension. The key to the success of model tracing in problem solving is the ability to identify and track the cognitive processes involved in solving problems. This requires the development of models that accurately represent the cognitive processes involved and the ability to track the learner's performance and progress.

19.4.2.3. Model Tracing in Reading Comprehension
Model tracing can also be used to develop adaptive tutors for reading comprehension. In this domain, the tutor tracks the learner's reading progress and provides feedback and guidance to help the learner improve their comprehension skills. The tutor can be used in a wide range of domains, from elementary reading to college-level reading. The key to the success of model tracing in reading comprehension is the ability to identify and track the cognitive processes involved in reading comprehension. This requires the development of models that accurately represent the cognitive processes involved and the ability to track the learner's reading progress and comprehension.

19.4.2.4. Model Tracing in Learning Environments
Model tracing can also be used to develop adaptive learning environments that provide feedback and guidance to help learners improve their knowledge and skills. These environments can be used in a wide range of domains, from K-12 education to higher education. The key to the success of model tracing in learning environments is the ability to identify and track the cognitive processes involved in learning. This requires the development of models that accurately represent the cognitive processes involved and the ability to track the learner's progress and performance.
III. SOFT TECHNOLOGIES, INSTRUCTIONAL AND INFORMATIONAL DESIGN RESEARCH

19.4.3. 1990s: Great Debates

The four ITS epics soon may be broadly characterized as:
1. How much learner control should be allowed in a system?
2. Should learners interact with ITS individually or collaboratively?
3. Is learning situated, unique, and contextual, or is it more abstract and generalized?
4. If an instruction processing model or ITS can be evaluated.

19.4.3.1. Degree of Learner Control.

The debate over the amount of learner control that should be a part of the instructional process has raged for many years (see 7.4.6, 12.3.3, 14.6.2, 22.5.5, 23.3.2, Chapter 33). On the one hand, there are those who argue that ITS are even more effective when they are allowed to make decisions about the instructional material presented to the user. On the other hand, there are those who believe that ITS should be more interactive and provide additional support to the learner. The debate continues to this day, and the results of the study are still not clear.

19.4.3.2. Authoring Systems.

The creation of computer-based educational tools has become increasingly popular in recent years. This is due to the increasing availability and affordability of computers, as well as the growing recognition of the benefits of computer-based instruction. The goal of authoring systems is to provide the analyst and instructional designer with a user-friendly tool for creating instructional materials. An example of one such system is the Authorware system developed over the last decade by the University of Nebraska.

Quite powerful CBT systems have been made available over the years. Research, beginning in the 1980s, attempted to adopt such systems as authoring tools for developing ITS. Miller and Lucado (1982) were among the first to design instructional systems that used the power of CBT authoring tools with the technologies of ITS. Their prototypes were designed to be used on a computer terminal and showed great promise.

More recent developments in authoring tools have focused on integrating ITS into existing CBT systems. For example, the use of CBT authoring tools to create ITS-based training systems is becoming increasingly common. This is due to the increasing availability of powerful authoring tools and the growing recognition of the benefits of combining these technologies.

In conclusion, the development of CBT authoring tools and ITS has led to the creation of powerful instructional systems that can be used in a variety of educational settings. The integration of these technologies is expected to continue to increase in the future, as educators and instructional designers seek to create more effective and engaging learning environments.
by combining apprenticeship training with intelligent instructional supports. (Kajali & Leong, 1992. 1993. and Egan, Katz, & associates. 1992; see 7.5.4.) These systems support greater learner initiative because the apprentice learns by doing. These systems require a reflective, collaborative approach anchored in experience; and the coach provides knowledge within an applicable context. Intelligent systems are developed with many of the characteristics of human apprenticeships, and performance can be easily assessed. Through replay and comparison with the expert performance, this approach also supports trainee analysis of performance. Solomon (1993) supports the trend of moving away from building traditional ITSs and towards the design of systems as cognitive tools. He sees cognitive tools manipulated by students as instruments that promote constructive thinking, transcending cognitive limitations, and making it possible for students to engage in cognitive operations they wouldn't otherwise have been capable of. Some ITSs programs make more diagnostic and tutorial decisions for the student; therefore, they are not really cognitive tools because they are not designed to upgrade students' intelligent engagements" (p. 180). Also, in accordance with the notion of computers as learning tools, learners should have the option to alter the degree of control themselves, from none (e.g., didactic environment) to maximum (e.g., discovery environment), as necessary. By shifting toward increased learner control, are individuals being more active or exploratory by nature being penalized or handcuffed? Stone and Glass (1990) investigated individual differences in learning from a discovery environment (stimulus) and found that individuals who demonstrated systematic, exploratory behaviors (e.g., recording baseline data), the number of changes made during experiments, and the number of changes made during experiments, were more successful in learning than those who revealed less systematic behavior. On the basis of that finding, they hypothesized in a different study (using an electricity tutor) that high-exploratory individuals would learn more from an interactive environment (stimulus) than from a more direct, applied environment (controlled to an interactive rule). A person who is highly exploratory on a mental task was defined as a person whose behavior was characterized by a large number of changes in a given context (e.g., number of times and length of time spent changing a resistor value, using the online volume, or assessing). Subjects were randomized to one of two learning environments, and the data were analyzed post hoc. The hypothesis that learning style by aptitude for aptitude interaction (AT) (see 22.3.3) was supported by the data (Stone, 1993b). So, discovering learning designs do not suit everyone equally well. For some, they provide a real bad fit. To determine whether this kind of frame style by aptitude interaction is replicable, Stone (1994) conducted a confirmatory test of the same ATI, reported above. Subjects were placed in a context of two environments based on the decision made during the previous study. And in the AT, the Alf was confirmed (see 11.4.4, 22.3.4, and 3.3 for more on ATI).

In conclusion, a split between too much and too little learner control is probably the best for an optimal ITS learner environment. Furthermore, this information should not be fixed, but rather be adaptable to the particular learner's needs. Finally, learners should have some input into the design of the environment, at least in the design of the environment, at least in the design of the environment, at least in the design of the environment, at least in the design of the environment, at least in the design of the environment. Our next step is to assess whether or not interactive learning is more effective for other domains or processes. We're not specifically address these topics in the following discussions, they should be kept in mind (also refer to Chapter 6, 7.4.3, 23.4, Chapter 25, 25.4.4). Individual vs. Collaborative Learning: Traditionally, ITS have been designed as single-user learners. Bloom (1984) and others have presented compelling evidence that individualized tutoring (using human tutors) engenders the most effective and efficient learning across an array of domains (see also Stone & Regan, 1990; Woolf, 1988). Furthermore, intelligent tutoring systems simulate the principles of individualized instruction better than anything else. In his oft-cited 1984 paper, Bloom presented a challenge to instructional researchers that has been called the "two-sigma problem." The goal is to achieve a learning environment that is significantly more successful in stimulating children's learning to the point of individualized instruction with tutoring over traditional instruction methods. So far, this goal has yet to be attained using individualized ITS. As a result, an ongoing research trend is collaborative learning, the notion that students, working together, can learn more and learn better, especially when they bring complementary, rather than overlapping, contributions to the joint enterprise (Cobb & Hills, 1989). Collaboration is described as "all individuals work together to negotiate and share meanings relevant to the problem-solving task at hand" (Traylor & Kocherla, 1993, p. 229), and is distinct from cooperation, which refers to the division of labor required to achieve some task.

Two empirical questions remain in this chapter: (1) Are ITS better for one task? Can intelligent computer systems support collaborative learning environments more effectively than beginning to light on both of these questions. For example, many researchers have shown immediate gains in knowledge and skill acquisition from learning environments (e.g., Illinois Science Laboratory and Project 18), (1988), (1989), and 1993; and the 1993 Journal of Artificial Intelligence and Education, 4 (1) (see 12.5.3.4.7.8.9). Obviously, one believes in the collaborative cognition or the traditional information processing models has implications for the design of the ITS. To illustrate this distinction, the following sections explore a constructive view of cognition and the implications of this view for the design of the ITS. To illustrate this distinction, the following sections explore a constructive view of cognition and the implications of this view for the design of the ITS.
process, enhanced by experiential involvement with the subject matter, that is situated in real-world contexts and problems. Furthermore, the system has a well-defined curriculum in accordance with popular learning theory.

According to constructivists, learners actively construct new knowledge rather than simply receiving information. Indeed, constructivists believe that education should foster the development of critical thinking and problem-solving skills. These skills are essential for success in the real world and are not easily acquired through traditional teaching methods.

As a result, educational technology has become increasingly popular as a way to facilitate learning and development. Educational technology includes a wide range of tools and techniques, such as multimedia presentations, simulations, and interactive software. These tools can help learners to construct knowledge and develop new understandings in a more engaging and effective way.

In conclusion, the use of educational technology can enhance learning and development in a variety of contexts. However, it is important to ensure that these tools are used effectively and that they are integrated into a well-defined curriculum. By doing so, educators can help learners to construct knowledge and develop new understandings in a more engaging and effective way.
19. INTELLIGENT TUTORING SYSTEMS: PAST, PRESENT, AND FUTURE

19.5.1.4.actus L. (1943) developed an ITS designed to help an individual's scientific inquiry skills within micro-world environment for learning scientific principles. The actus L. aimed to enhance students' understanding of scientific concepts and applications, and generalization of problem-solving skills.

The curriculum embedded by the tutor was equivalent to about half a semester of introductory physics. This is the curriculum equivalent to about 7 weeks or 21 hours of instruction time. Adding 2 hours per week for computer laboratory time to the total 81 hours of instruction contributed to a half-semester of physics. The instructional strategy was analyzed for the time it would be at least 35 hours. In the study discussed above, subjects completed the tutor in considerably less time (i.e., mean = 12 hours, SD = 5 hours, normal distribution). So, in average, it would take about 3 times as long to learn the same factual material in a traditional classroom and laboratory environment as with this tutor (i.e., 35 vs. 12 hours).

While all subjects finished the physics terminology in less time compared to time needed to complete the curriculum in traditional instruction methods, there were large differences in learning rates found at the end of the tutor. For those subjects having prior physics experience, the maximum and minimum completion times were 29.2 and 2.8 hours, a range of more than 10x. In addition, while all 260 subjects successfully solved the various problem-solving problems in the tutor's curriculum, their learning outcomes reflected differing degree of achievement. The range of the three achievement scores was 55.8% (SD = 19, normal distribution). The range from the highest to the lowest score, 96.7% vs. 77.8%, represented large between-subject differences at the time of the final test. To account for these individual differences in outcome performance. Stein (1994) found that a measure of working memory capacity, specifically attentional capacity (i.e., problem identification, analysis, and sequencing of elements), and some learning style characteristics (i.e., seeking for help and learning preferences) accounted for 60% variance.

19.5.1.5. A study by Smith and Glasner (1991) developed at ITS designed to teach an individual's scientific inquiry skills within a micro-world environment for learning scientific principles. The actus L. aimed to enhance students' understanding of scientific concepts and applications, and generalization of problem-solving skills.

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19.5.2. Conclusions from the Six Evaluation Studies

These evaluation results all appear very positive regarding the efficacy of ITSs. However, there is always a limit to what it has involved with the publication of unanimous evidence of successful instructional interventions. We are
19.6.1 Future: Immersive Learning Environments Evolve from ITS

Alden (age 14) walked through his high school and excitedly told his teacher that he had just discovered a new learning environment based on virtual reality. His teacher, Ms. Thompson, was amused and interested in this new approach. She had heard about virtual reality in a recent meeting at the school district. Ms. Thompson was intrigued by the potential of virtual reality in education and decided to explore its possibilities further.

Virtual reality (VR) technology offers a unique opportunity for education. It provides a highly immersive experience that can simulate real-world environments. This can be particularly useful in subjects such as science, history, and language learning.

19.6.2 Future: Traditional ITS Disappear; Specific Cognitive Tools Dominate

Whitney (age 14) arrived at her classroom and found a new interactive computer program waiting for her. The program was designed to teach her about scientific concepts in a fun and engaging way. Whitney was excited to start using the program.

The program uses specific cognitive tools to enhance learning. Whitney found that the visual and auditory elements of the program helped her understand complex concepts more easily. She especially enjoyed the interactive quizzes and games that kept her engaged.

In conclusion, virtual reality and specific cognitive tools are shaping the future of education. These technologies offer new possibilities for immersive learning experiences that can enhance student engagement and understanding.
domain, but also possessing a wide spectrum of general problem-solving skills. This same applies for ITS. Rather than attempting to build an unimpressive tutor, a more fruitful approach is to create a common collection of domain-oriented tutorials, with a common interface, with a common set of principles, and finally, to assimilate this future and the metaphor and simulate the system (e.g. the gestalt of the literary tradition), or simulate the system (e.g. the gestalt of the literary tradition), we will first make a functional change on how we think about education. Our current concept of education has shown only relevant for those between ages 5 and 18, and no longer appropriate. Education should be for everyone, all ages, and available in all places.

19.6.4 Future: Individualized Learning Is Out, Collaborative Learning Is In
Sims, Neita, Fernando, Sara, Kevin, and Uri comprise "team 3." They are between the ages of 16 to 22 (college sophomores). In their sociology class, there are two professors and five teams, each team reflecting an optimal mix of inputs, gender, learning styles, personality types, and ethnic backgrounds. They are all gathered up for their on-line tern on "racial prejudice." The six students are transported to Birmingham, Alabama. In a bar August day in 1955, in reality, only Sara and Kevin are African-American, but in this lesson, all six are transferred into "Negro" (as they're called in 1955). The lesson requires those to take a role in the "Whites Only" part that has a more prominent role, the others (standing in the pool, then go home to their imprisoned Mississippi in the outdoors of town. Problems arise immediately in this compelling simulation when they heard the bar staff. Automatically, they all sit down in the first row, and all are only those other sides on the bus, sitting in the middle section. The white bus driver merely informs them to "move to the back." whereas the rear (team 1's viewpoint) leader publicly asks "Why?" When she gets slapped for her insubordination. No one steps in to say "But Sara points to the bus driver out some very ugly sentiments about dollars and the mixed crowd on the other side. They give out their reasoning face and posture that he's about the microscope. And we decide to move slightly to the back of the bus. During the ride, they discuss their experiences (what they feel, what they could have done differently). What caused this state of affairs? Sims and Kevin contribute valid psychological discussion to the discussion from personal facts related to them by their grandparents and great-grandparents. Finally they settle in the back, and things really go downhill in the pool, they're called "dirty" and worse, and the simulation makes them think as one of racist policies. Afterward, team 3 reviews and discusses all of the lesson, and the session provides information, as simulated. After this situation, their lesson has been learned.

The most fitting direction this future is the belief that collaborative learning is more successful than individualized learning. VR enables an enhanced environment with conversations that have different question, background, or skills, know more about some

19.6.5 Future: ITS Approach Continues, Becoming Truly Interactive
Kim (age 16) arrives at the math lab where he sits in front of a computer that is going to help him learn to solve algebraic word problems better. Today's focus is on these trouble-some distance-two-time problems. After stating his name, the computer accesses Kim's records, focusing on his current strengths and weaknesses (i.e., not only his higher-level aptitudes but also the lower-level production that he's acquired and not yet acquired). Beginning with a review of concepts and skills that he learned before the ITS presents a problem that is just a bit easy for this group. The ITS then works on the correct solutions to the problem, along with a different solution that Ken insists to be the common-sense approach. Ken insists on it, as it pedagogically reduces the simulation, which elements should be added to and when. Ken states that he understands the mapping between the ITS model, the appropriate equation, and the relevant part of the word problem. The ITS shows Ken an algebraic word problem. This time he solves it correctly, without any supplemental training. Ken examines the options to play around with some input, such as, the function, the series, and the game for a whole to test his emerging understanding. He views his "score" of conceptual elements, and he seems a little frustrated about his progress, but the ITS reassures him that he is proceeding at a reasonable rate. Knowledge and control.

19.7 Conclusion
Most of the work described in the above sections, and the knowledge-based tutorials can support in the above scenarios, more controlled research must be conducted in three areas of intelligence: the domain expert, the student model, and the tutor. First, the domain expert must be able to define a theoretical model of that knowledge. Finally, the tutoring strategy must be considered to the point at which on-line tutor can implement
19.7 CONCLUSIONS

Before the computer age, the prevailing instructional approach was effective (e.g., one teacher transmitting knowledge to about 10 students), but we now reside in a computerized world. Initial implementations of CAI missed this pedagogical approach and, in some cases, do the currently popular model-training approach in sophisticated ITS. Do we need to change our educational philosophies or systems?

We have most of the components necessary to advance educational reform. Not only is there great need for change, but there are also powerful, affordable technologies available to support it. Misleading definitive answers to the psychological controversies (and earlier, basic research) are being replaced by more informative studies involving students with the subject matter. This "constructivist" view of learning allows students to achieve intellectual accomplishments that are possible only for more traditional pedagogical approaches (Collins, Brown, & Newman, 1989; Konold, 1997).

Table 19-2 contrasts old versus new approaches to instruction (from Means, O'Brien, Oliver, Mitchell, and Marhefka, 1989). The table provides a check list for future ITS research and implementation. That is, to get from "old" to "new" we need to open up learning environments that promote increased learner interaction and have learners become more active in the instructional process. We must provide learners with opportunities to use the computer as a tool to the fullest extent of the software available. Not only is it a beast, but also the entire basis of the computer. Nevertheless, as the technology rapidly changes, we need to be aware of the new and old approaches. The table is organized to guide the reader in the "new" approach.

Learners are not only computers, but they are also being trained to interact with the computer. The sophistication of the "old" and "new" approaches are compared; controlled studies have been conducted of attitude-treatment interaction; and so forth. For purposes of education, these ideas can be extended to other uses understandable. But for purposes of education, these ideas can be extended to other uses understandable.

TABLE 19-2. OLD VERSUS NEW APPROACHES TO INSTRUCTION

<table>
<thead>
<tr>
<th>Old Approach</th>
<th>New Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teacher-directed activities</td>
<td>Student-directed explanations</td>
</tr>
<tr>
<td>Didactic teaching</td>
<td>Interactive modes of instruction</td>
</tr>
<tr>
<td>Short instruction as a single subject</td>
<td>Embedded, multitasking, interpersonal interaction</td>
</tr>
<tr>
<td>Individual work</td>
<td>Collaborative work</td>
</tr>
<tr>
<td>Teacher as facilitator</td>
<td>Instructor as facilitator</td>
</tr>
<tr>
<td>Ability grouping</td>
<td>Interactive groupings</td>
</tr>
<tr>
<td>Assessment of factual knowledge and discrete skills</td>
<td>Performance-based assessment</td>
</tr>
</tbody>
</table>

19.1 INTELLIGENT TUTORING SYSTEMS: PAST, PRESENT, AND FUTURE

References

20. COGNITIVE TEACHING MODELS

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20.1 COGNITIVE TEACHING MODELS

Educational psychology and instructional design (ID) have had a long and fruitful relationship (Dick, 1987; Merrill, Reigeluth & Wilson, 1981). Educational psychologists like Gagne and Glaser have always shown an interest in issues of design (Gagné, 1968; Glaser, 1975); indeed, they helped establish instructional design as a field of study (see 18.3) (Gagné, 1987). Lumsdaine and Gager, 1960). In recent years, a growing number of cognitive psychologists have shown a renewed interest in design issues and have tested out their ideas by developing prototype teaching models. These teaching models differ from most educational innovations in that they are well-grounded in cognitive learning theory. Examples include John Anderson's intelligent tutors (Anderson, 1983) and Rossen and Palincsar's reciprocal teaching method for teaching reading (see Reutzel & Melton, 1990). Wilson and Colby (1991) reviewed a number of these prototype teaching models and related them to current ID theory. This chapter continues that agenda by reviewing a number of additional teaching models and drawing implications for the design of instruction.

Specifically, the purpose of the chapter is to:

1. Argue that the development and validation of teaching models is a legitimate research method and has been an important vehicle for advancing knowledge in learning and instruction.
2. Show how the development of cognitive teaching models compares to the development of traditional ID theory.
3. Review a number of cognitive teaching models, and discuss a few in detail.
4. Look for insights from these cognitive teaching models that relate to instructional design.
5. Identify issues for future research.

20.1.1 Instructional Psychology and Design: An Historical Overview

To provide a context for interpreting the chapter, consider the historical overview provided in Table 20.1.

The field of instructional design developed in the 1960s and early 1970s as a time when behaviorism still dominated mainstream psychology. ID shared these behavioral roots and at the time was closer to mainstream psychology. ID theorists such as Gagné, Briggs, Merrill, and Schaefer all were educational psychologists. With the cognitive revolution of the 1970s, instructional psychology differentiated itself from ID and drifted more to the cognitive mainstream, leaving ID relatively isolated with concerns of design. In a review of instructional psychology in 1981, Laura Resnick (who only a few years earlier had developed Gagné-style learning hierarchies) observed:

As interesting things have happened to instructional psychology: it has become part of the mainstream of research on human cognition, learning, and development. For about 20 years the number of psychologists devoting attention to instructionally relevant questions has been gradually increasing. In the past 5 years this increase has accelerated so that it is now difficult to draw a clear line between instructional psychology and the main body of basic research on complex cognitive processes. Instructional psychology is no longer basic psychology applied to education. It is a fundamental research on the processes of instruction and learning (Resnick, 1981, p. 660).

In her review, Resnick acknowledged that mainstream instructional psychologists had focused on issues of performance modeling and cognitive task analysis, neglecting the challenge of devising effective instructional strategies, models, and interventions. Even so, she did not look to the ID community to fill the need because "instructional design theory... which is directly concerned with prescribing..."