



The Cognitive Tutor: Applying Cognitive Science to Education

Carnegie Learning's Cognitive Tutor® programs represent an innovative application of technology, artificial intelligence and cognitive science. These programs give students the opportunity to receive individualized attention, maximizing the amount of time spent actively learning and mastering fundamental thinking skills. The Cognitive Tutor software monitors the status of each student's knowledge on a moment-by-moment basis and tailors course material for each student, based on these continual assessments.

The Cognitive Tutor is able to understand student knowledge and problem-solving strategies through the use of a cognitive model. A cognitive model represents the knowledge that an ideal student would possess about a particular subject. In a very real sense Cognitive Tutors can be said to understand the subject matter because they represent material the same way a student would, and they can use this representation to solve problems in a way that mimics student performance.

Theoretical Basis

Cognitive Tutor programs are different from other educational solutions because they have a sound theoretical basis in the science of how people learn. Our cognitive models are based on John Anderson's ACT-R theory of human cognition (c.f. Anderson, 1990, 1993; Anderson & Lebiere, 1998). Anderson, a founder of Carnegie Learning, member of the National Academy of Sciences and professor at Carnegie Mellon University, began work on this theory in the late 1970s and has refined it the years since. Regarded as one of the most robust and mature theories of cognition, Dr. Anderson's model is capable of representing a wide variety of human thinking (see <http://act-r.psy.cmu.edu/>).

Basic tenets of the ACT-R theory include:

- The knowledge required to accomplish complex tasks can be broken down into a large set of simple cognitive skills and facts.
- Cognitive skill becomes more fluent and robust through practice.
- Performance on one task will transfer to another task to the extent that the two tasks share skills.
- Knowledge comes in two types: declarative and procedural. Declarative knowledge includes facts, images and sounds. Procedural knowledge is an understanding of how to do things. All tasks involve a combination of the two types of knowledge. As we learn, we generally start out with declarative knowledge, which becomes proceduralized through practice. Procedural knowledge tends to be more fluent and automatic. Declarative knowledge tends to be more flexible and broadly applicable.
- Knowledge is highly interconnected.

Applying ACT-R to Education

Starting in the early 1980s, Anderson and his colleagues began developing the Cognitive Tutor technology to test the ACT-R theory's applicability to real-world learning.

The ACT-R theory has clear implications for the design of educational materials (Anderson, 2002; Bransford, Brown and Cocking, 1999). Materials should focus on helping students build appropriate conceptual representations and on strengthening the underlying cognitive skills required to master the target tasks. Specifically, educational materials should be effective if they:

- Are based on research that reveals the skills underlying the target domain of knowledge (Corbett, McLaughlin, Scarpinnatto and Hadley, 2000; Mark and Koedinger, 1999; Koedinger and Anderson, 1990).
- Present instruction, tasks and experiences that allow students to learn and practice these skills (Corbett and Anderson, 1992, 1995a; Ritter and Anderson, 1995)
- Provide immediate feedback, so that errors are attributable to specific cognitive skills (Corbett and Anderson, 1989; Mathan and Koedinger, 2003)
- Continually assess students' knowledge of each of the skills, in order to focus each student's instruction on the skills that that student needs to learn and avoid spending too much time on skills that the student has already mastered (Anderson, Conrad and Corbett, 1989; Corbett and Anderson, 1995b)
- Build on what students already know, so that new declarative knowledge is well incorporated into students' knowledge networks (Alevan and Koedinger, 2002; Koedinger and Anderson, 1998)
- Ground procedural activities in conceptual understanding, so that this knowledge can be proceduralized (Rittle-Johnson and Koedinger, 2001; Koedinger and Terao, 2002)

Each of these principles has strong empirical support in research conducted on Cognitive Tutors and in the specific application of this research to the Cognitive Tutors for mathematics. Our development processes have emphasized constructing tasks that make the connection between conceptual and procedural knowledge. Students are encouraged to actively engage with the mathematics, so that they can strengthen their skills and apply them in different contexts. Cognitive modeling has proven to be a powerful technique for discovering the skills underlying tasks, monitoring individual student mastery of these skills and customizing curriculum so that each student gets the right amount of practice on each of the skills.

Proven Effectiveness

Careful research into how people learn and the embodiment of sound educational principles into a Cognitive Tutor has proven to dramatically improve student learning. Some of the most compelling results include:

Cognitive Tutors improve teachers' ability to reach students

In Moore, OK, teachers were directed to use Cognitive Tutor Algebra I for some of their classes and to use a traditional textbook for others. Despite the fact that Cognitive Tutor was new to the district and the textbook had been used for years, students who were in Cognitive Tutor classes outperformed their peers on both standardized tests and course grades.

This study was recognized by the US Department of Education's What Works Clearinghouse as providing the strongest evidence of effectiveness for a mathematics curriculum. A summary of this report is available at http://www.carnegielearning.com/research/research_reports/ok-01-01.pdf. For the full report, see Morgan and Ritter (2002).

Cognitive Tutor improves scores on high-stakes state exams

The Miami-Dade County school district uses Cognitive Tutor for some classes in ten high schools. An independent analysis of 2003 FCAT scores showed that students who used Cognitive Tutor significantly outscored their peers on the exam. A summary report of this study is available at http://www.carnegielearning.com/research/research_reports/fl-03-01.pdf. For the full report, see Sarkis (2004).

Cognitive Tutor improves student attitudes towards mathematics

The Moore, OK study also included a survey asking students to rate whether they felt confident in their ability to learn higher level mathematics and whether they felt that they understood how mathematics was useful outside of the classroom. On both confidence and perceived usefulness of mathematics, Cognitive Tutor students gave higher ratings than their peers.

Cognitive Tutor helps students improve their problem-solving and critical thinking skills

In studies conducted in Pittsburgh and Milwaukee, students were measured both on standardized tests (SAT and Iowa) as well as performance-based problem-solving. Cognitive Tutor students significantly outscored their peers on the standardized tests, but the difference in performance was particularly pronounced on the problem-solving exams, where the Cognitive Tutor students outscored their peers by 85%. A summary of these results is available at http://www.carnegielearning.com/research/research_reports/cmu_research_results.pdf. A more complete analysis of this data is available in Koedinger, Anderson, Hadley and Mark (1997).

Cognitive Tutors show strong results with disadvantaged populations

The previously-cited Miami-Dade County study found that 35.7% of Exceptional Student Education students who used Cognitive Tutor passed the FCAT, as compared to only 10.9% of such students using a different curriculum. For students with Limited English Proficiency, 27% of Cognitive Tutor students passed the FCAT, as opposed to only 18.9% of such students in another curriculum.

A study in Kent, Washington (outside of Seattle) found a pre- to post-test improvement on the NWEA's Achievement Levels Test (ALT). English Language Learners who used Cognitive Tutor improved 31 points from pre- to post-test, as opposed to a 17-point improvement for such students using a traditional curriculum. The study also showed that students receiving free or reduced lunch improved 19 points if they used Cognitive Tutor, as opposed to 14 points using a traditional curriculum. A summary of this study is available at http://www.carnegielearning.com/research/research_reports/wa-04-01.pdf.

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