SCIENCE BRIEFS

Valerie J. Shute, PhD

Learners and Instruction: What's Good for the Goose May Not Be Good for the Gander

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Dr. Shute is the recipient of several awards and honors, including most recently, the Harry G. Armstrong Scientific Excellence Award. She has written many journal articles and book chapters and, in 1992, she was coeditor of the book, Cognitive Approaches to Automated Instruction.

A simple and intuitively plausible precept that has been around for many years is that some learners benefit from instruction provided one way whereas others learn more if instructed a different way. In fact, the idea that teaching is best accomplished by tailoring instruction to student traits is ancient. This idea has been described in the 4th-century B.C. Chinese *Xue Ji*, in the ancient Hebrew *Haggadah of Passover*, and in the 1st-century Roman *de Institutione Oratoria*. Such relationships are called *aptitude-treatment interactions (ATI)*. *Aptitude* is defined in the broadest sense as a person's incoming knowledge, skills, and even personality traits. *Treatment* refers to the condition or environment that supports learning.

The goal of ATI research is to provide information about learner characteristics that can be used to select the best learning environment for a particular student. Figure 1 depicts the theory of ATI as well as a prototypical graph of an aptitude-by-treatment interaction.

Although hundreds of studies have been conducted to look for ATIs (especially during the 1960s and 1970s), it has been surprisingly difficult to verify empirically learner-by-treatment interactions. In 1977, Cronbach and Snow wrote an excellent review of ATI research, and it's clear from reading their book that a major problem with those

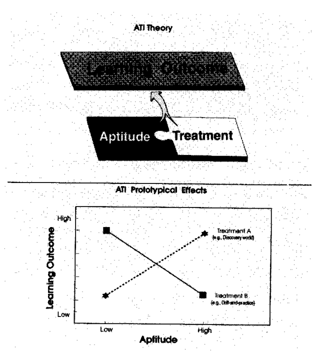


Figure 1. ATI Theory and Prototypical Graph

older ATI studies concerned data "noisiness." That is, experimental data obtained from classroom studies contained extraneous, uncontrolled variables, such as differing teacher personalities, instructional materials, and classroom environments. Recently, however, there has been renewed interest in examining the ATI issue using computers as controlled learning environments. The following is a summary of a study I conducted in which each part of an aptitude-treatment interaction is described and measured in a controlled manner.

Aptitude

Individuals come to any new learning task with often large differences in knowledge and skill, learning style, motivation, and cultural background. These aptitudes affect what is learned. Here, I will focus on a particular learning style measure, *exploratory behavior*, as evidenced during interaction with an intelligent tutoring system (ITS) instructing principles of electricity. That is, during the course of learning, a student attempts to solve progressively difficult problems with DC circuits presented by the ITS. However, at any given time, he or she is free to do other things in the environment, such as read definitions of concepts, take measurements on the on-line circuit, or change component values (e.g., voltage sources or resistors). All explorations are optional and self-initiated. To quantify an individual's exploratory behavior, I created proportions--the ratio of time spent engaged in exploratory behavior divided by the total time on the tutor. This procedure was necessary to control for differential tutor completion times, which ranged from 5 to 21 hours.

Treatment

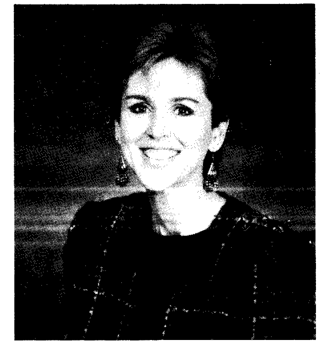
In addition to aptitude, learning environment (i.e., treatment condition) may also affect learning outcome. One way learning environments differ is in the amount of control the student has. This can range from minimal (e.g., rote or didactic environments) to almost complete control (e.g., discovery environments). Two opposing perspectives, representing the ends of this continuum, have arisen in response to the issue of the optimal learning environment. One approach is to develop straightforward learning environments that "spoon-feed" information to the learner; the other requires the learner to derive concepts and rules on his or her own. The disparity between positions

becomes more complicated because the issue is not just which is the better learning environment, but rather which is the better environment for different types of persons--an ATI issue. This very issue motivated the experiment I will describe in which I created environments representing the ends of this control continuum (i.e., *rule-application* and *rule-induction*).

The two learning environments were created from an ITS instructing basic principles of electricity as a complex but controlled learning task. These two instructional environments differed only in the feedback delivered to the student. For instance, in the rule-application environment, feedback clearly stated the variables and their relationships for a given problem. This was communicated in the form of a rule such as, *"The principle involved in this kind of problem is that current before a resistor is equal to the current after a resistor in a parallel net."* Subjects then proceeded to apply the rule to solve related problems. In the rule-induction environment, the tutor provided feedback that identified the relevant variables in the problem, but the learner had to induce the relationships among those variables. For instance, the computer might give the following feedback, *"What you need to know to solve this type of problem is how current behaves, both before and after a resistor, in a parallel net."* Subjects in the rule-induction condition, therefore, generated their own interpretation of the functional relationships among variables composing the different rules.

Learning Outcome

I also created four posttests measuring a range of knowledge and skills acquired from the tutor. All tests were administered on-line after a person finished the tutor. The first test measured declarative knowledge of electrical components and devices and consisted of both true/false and multiple choice questions. The second posttest measured conceptual understanding of Ohm's and Kirchhoff's laws. No computations were required, and all questions related to various circuits. The third posttest measured procedural skill acquisition. Computations were required in the solution of problems. The student would have to know the correct formula (e.g., voltage = current X resistance), fill in the proper numbers, and solve the equation. Finally, the fourth test measured a person's ability



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to generalize knowledge and skills beyond what was taught by the tutor. This required both conceptual understanding of the principles as well as computations.

Experiment

Over 300 subjects (84% men, 16% women) completed this study on the acquisition of basic principles of electricity. Each subject participated for 7 days. All subjects were high school graduates (or equivalent) with a mean age of 22 and an age range from 18 to 28. Subjects were obtained from two local temporary employment agencies, none had any prior electronics instruction or training, and all were paid for their participation.

I randomly assigned subjects to one of the two environments (rule-application vs. rule-induction), and both versions permitted subjects to engage in the optional exploratory behaviors described earlier. Exploratory behaviors were monitored by the computer and later quantified for post hoc ATI analysis. Although I originally believed that the inductive environment would support (if not actively promote) the use of exploratory behaviors, results showed no differences at all between environments; the mean proportions were 0.12 and 0.13 in the rule-application and rule-induction environments, respectively. Finally, learning outcome was defined as the percentage of correct scores on the four tests, combined into a single outcome factor score. I hypothesized that learners exhibiting greater exploratory behavior would learn better if they were assigned to the inductive environment and that less exploratory learners would benefit from the more structured application environment. Results supported this hypothesis, showing a significant aptitude-treatment interaction (see Figure 2). Furthermore, when aptitude was excluded, treatment had little impact; the average posttest factor score for the rule-application environment was 0.08 (SD = 1.1), and it was -0.08 (SD = 0.9) for the rule-application environment.

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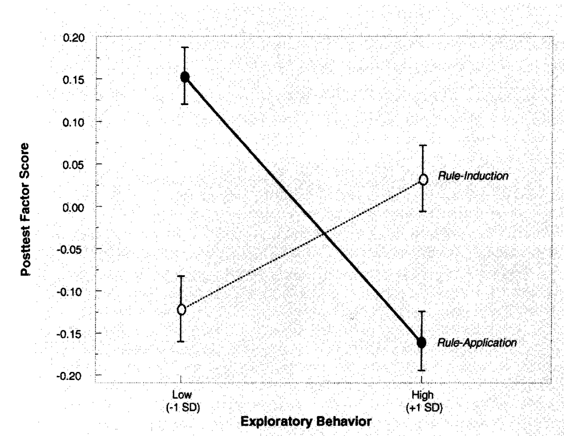

Figure 2. Exploratory Behavior by Learning Environment

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Learners and Instruction

What are the implications of these findings? As psychologists, engineers, and educators concerned with instruction, our goal should be to maximize learning for as many individuals as possible, at a reasonable cost. Results from this study provide preliminary information about which learning environments are more suitable for which learners (for this particular domain): Low-exploratory individuals learned significantly better in a structured rule-application environment, and high-exploratory individuals learned significantly better in an inductive learning environment. There was no clear optimal learning environment to build into a tutor. In fact, there were no significant differences between learning environments on any outcome measure when aptitude was not included in the equation.

To use ATI methods in an instructional setting, one needs to make certain critical decisions: Which aptitudes should be measured before or during instruction? Which treatment variables should be manipulated? And which learning outcome and efficiency measures should be used? A taxonomy of learning skills, which my colleague Pat Kyllonen and I developed, can assist in answering some of these questions. This taxonomy defines a four-dimensional space involving learner attributes, learning environment, desired knowledge outcome, and the subject matter.

In conclusion, most, if not all, ATI studies in the literature are exploratory, as is the one reported here. That is, data are collected, and ATIs are tested, albeit post hoc, typically as part of general "ATI fishing expeditions." But to test a specific hypothesis, a confirmatory data analysis technique should be used. Confirmatory tests for ATI are critical, especially if we want to validate claims that ATIs are real and use results from ATIs to maximize learning. I've just completed the first large-scale *confirmatory* study involving the ATI reported herein, and the ATI was replicated. Thus, the next generation of ATI research may ultimately get out of the laboratory and into the real world. ■

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