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INDIVIDUALIZED AND GROUP APPROACHES TO TRAINING

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INTRODUCTION

The purpose of this chapter is to provide a survey of the current state of knowledge regarding human- and computer-based instruction within individualized and group approaches to training. A few of the questions we address include: What is individualized training?; what are some of the ways it is achieved by humans and by computers?; and how does computerized instruction affect learning outcome and efficiency in relation to traditional classroom approaches? Also, what does group training refer to, what are some of the effective approaches and variables, and how can it be done better?

To lend a sense of coherence to this endeavor, and to make the chapter more useful to those with an applied orientation to training, we have included summary tables at the end of each major section. These tables provide the most specific training recommendations we can offer, given the literature that was reviewed and included herein. The reader should keep in mind, however, that all such recommendations are constrained by the fact that each study was based on empirical research conducted within a specific context, involving a distinct domain, and using particular materials, technologies, and techniques. Thus, generalizations of findings to new settings should be made with caution. We felt obliged to provide explicit suggestions, but they should be viewed as handy guidelines, rather than universally applicable laws of training. More general decision rules are currently impossible; there are simply too many variables that have not yet been systematically examined, either singly or interactively.

Many of the subsections in this chapter could easily have been expanded into stand-alone chapters. In attempting to cover the most significant topics related to individualized and group training within our space limitations, we made an explicit decision to strive for breadth of coverage, occasionally at the expense of depth. Where this is the case, we provide appropriate references, so that readers can readily obtain more detailed information about technical terminology, constructs, studies, theories, or training approaches. We have, nevertheless, clearly noted in the body of this chapter certain key areas that cry out for an investigative mind or two to travel down their paths.

OUTLINE OF THE CHAPTER

We begin with a brief section devoted to defining a few important terms. The remainder of the chapter is organized into four major sections. The first section provides an overview of issues related to *adaptive instruction.* The discussion includes two specific types of instructional adaptation and three different approaches to adaptive training. We review the relevant literature on each approach and provide illustrative studies, where appropriate. The second section of the chapter covers *individualized training.* It begins with a subsection describing individual-differences research, as it relates to the major components of contemporary learning and instructional theory. We also compare the relative effects of human- and computer-delivered instruction on individualized training. The third major section in this chapter reviews issues and approaches surrounding *group training* (e.g., collaborative training environments, social constructivism). It includes a review of the literature related to group dynamics: the identification of variables influencing how well a group interacts, as well as the relationships among those variables. We conclude this section with a discussion of computer-delivered instructional systems for groups of trainees. A fourth section presents important issues that should be considered when designing a training curriculum. Some of the topics found there address relationships among the task, training goals, and training approach, as well as the role of the teacher or trainer. We end with some concluding thoughts and sample attempts at using the research presented within this chapter to make informed decisions about maximizing training.

DEFINITION OF KEY CONCEPTS

Researchers and practitioners in different fields (and occasionally those in the same field) use terms that can have more than one meaning. For instance, within the field of psychology, a psychometrician construes the concept of "individual differences" as persistent and measurable aptitudes that distinguish groups of people. These aptitudes may then be used to predict performance on some learning task, with the focus on the *differences*. But for a designer of computer-assisted instruction, "individual differences" refers to the degree and rate to which an individual transforms from a novice to an expert. Here, the focus is on the *individual*. Finally, to an experimental psychologist, "individual differences" are often construed as *noise*, and the goal is to attenuate them. To standardize terms used in this chapter that are potentially subject to multiple interpretations, we begin by specifying exactly how we define important concepts, including education and training, instruction, individual differences, and learning.

Education and Training

These two terms are sometimes used interchangeably, but most teachers and trainers would agree that a distinction is important when speaking precisely. Although Tobias and Frase have already addressed this distinction in the introductory chapter, we feel it is beneficial to share our own working definitions of the two terms as they relate to this particular chapter. We define *education* as a systematic program of instruction with the goal of instilling knowledge about some domain(s) in an individual or group. *Training*, on the other hand, refers to a systematic program of instruction with the goal of enhancing the proficiency of an individual or group in relation to some skilled endeavor. Although education and training both impart knowledge and skill, the proportion of imparted knowledge is higher for education, and the proportion of imparted skill is higher for training. Thus, the difference between the two should be considered a continuum, rather than a dichotomy. One way to make the distinction more concrete is to answer the following question: Would you prefer that your child participated in sex education or sex training courses at school?

Instruction

The astute reader is likely to have noted that the term "instruction" was used, seemingly synonymously, in the definitions of both education and training. This reflects the nature of the term itself, in that we consider it to be universally applicable within any systematic attempt to impart skill or knowledge to another person. The particular "flavor" of a given instructional effort determines whether it is education or training that is taking place.

Individual Differences

You will see occasional references throughout this chapter to two different aspects of the individual differences construct: "between" (*inter*) and "within" (*intra*). Interindividual differences relate to aptitude disparities among persons (e.g., in intelligence, spatial skills, perceptual abilities), as well as other differences related to demographic variables, such as differences in prior experience or education. When the term "individual differences" is used by itself, it is this definition that is typically meant. For instance, "There were great individual differences among trainees' educational and socioeconomic backgrounds." Intraindividual differences research examines changes that transpire within a person as he or she progresses from novice to expert in acquiring some knowledge or skill. Issues here relate to an individual's learning ability—his or her personal learning curve. Intraindividual changes may refer to the progression of one's conceptual understanding or procedural skill over time, as well as to fluctuations in performance related to diurnal variations in motivation, affect, and so on. Later in this chapter, we argue that both inter- and intraindividual differences should be considered when designing instruction for training purposes.

Learning

The effectiveness of education or training may be gauged by the degree to which a learner acquires relevant knowledge or skill. This acquisition is generally regarded as a constructive activity where the construction can assume many forms. Individuals differ in how they learn (processes) as well as what they learn (outcomes). Bower and Hilgard (1981) have summarized the process/outcome relationship "as a process is to its result, as acquiring is to a possession, as painting is to a picture" (p. 1). But painters differ—they have diverse experiences, use different painting techniques and, given the same canvas and palette, will produce quite different pictures. The same is true for learners; different outcomes of learning (e.g., declarative knowledge) reflect differences in general learning processes (e.g., associative learning skills), specific learning processes (e.g., attention allocation), and incoming knowledge and skill. Thus, the operational definition of learning used in this chapter is that *learning is a process of constructing relations*, and these relations become progressively more complex, and at the same time more automatic, with increased experience and practice.

The processes of learning may be viewed from either of the two perspectives discussed above, namely, inter- or intraindividual differences. The perspective depends on whether one is interested in group differences (e.g., for prediction and classification purposes) or in individual development (e.g., for mastery learning and adaptive instruction). The *nature* of learning also has different perspectives, represented by situated cognition and the traditional information-processing model. Greeno (1998) contends that learning occurs within systems in which people interact with each other and with material, informational, and conceptual resources in their environments. The basic premise is that learning involves socially-organized activities. In contrast, Anderson, Reder, & Simon (1996, 1998) represent the information-processing view and rebut this situated notion of learning: "Presumably, the situated view would correspondingly not deny that there are individuals interacting in all situations, that these individuals have minds, that much of their individuality comes from the (socially and individually acquired) knowledge contained in those minds, and that they are not just cogs in a social wheel" (1996, p. 20). From Anderson et al.'s perspective, progress in understanding the social aspects of learning can be made by analyzing the social situation into relations among a number of individuals and to study the mind of each individual and how it contributes to the interaction.

The position on learning adopted in this chapter is intermediate between the two perspectives just described. We see at least three main elements in a unified theory of learning and instruction: (1) analysis of the initial state of knowledge and skill; (2) description of the desired or end state of knowledge and skill (learning outcome); and (3) explanation of the learning processes that serve to transition a learner from initial to desired state accomplished in an instructional setting (see Figure 7-1). A fourth component, the specific collection of techniques and materials used in any particular instructional treatment, is sometimes included in such models (Glaser, 1976; Glaser & Bassok, 1989; Snow, 1989). It is not found in Figure 7-1 because the figure is meant to represent only the characteristics of, and changes within, the learner. Interindividual differences in learning arise from disparities among learners on any one of the initial knowledge and skill components, whereas intraindividual differences address how a person makes the transition from the initial to the final state. A more detailed explanation of this figure can be found in a subsequent section of this chapter, "Individualized Training."

ADAPTIVE INSTRUCTION

A simple and intuitively plausible precept that has been around for many years is that some learners benefit from instruction provided one way while others learn more if instructed a different way. Adaptive instruction refers to the real-time modification of the instructional curriculum, learning environment, or training regimen to suit different student characteristics. This has been a persistent goal among educators (Bloom, 1968; Corno & Snow, 1986; Cronbach & Snow, 1977; Regian & Shute, 1992a; Tobias, 1989). In fact, the idea that teaching is best accomplished by tailoring instruction to student traits is quite ancient. The idea is described in the fourth-century B.C. Chinese *Xue Ji*, in the ancient Hebrew *Haggadah of Passover*, and in the first century Roman *De Institutione Oratoria* (Snow & Yalow, 1982). Instruction may be altered macroadaptively or microadaptively, or both, depending on whether the decision is being made in response to unique characteristics of a single learner (e.g., unfamiliarity with a particular component skill) or to trait characteristics that are known to interact with certain instructional techniques to influence training outcomes.

*Macro*adaptive instructional decisions occur before training actually begins (see Shute, 1993a and Snow, 1992 for more on this topic). Macroadaptation involves first collecting trait data (e.g., cognitive ability data) on the target learner(s), then using that information to make an informed decision regarding the type of instructional environment best suited to those characteristics. For instance, a common empirical finding is that high-cognitive-ability learners thrive in an exploratory environment, whereas low-ability learners need the structure of a more didactic environment to facilitate the acquisition of knowledge and skills. If you know where a trainee or group of trainees falls along the cognitive-ability continuum, you can place them in a more appropriate environment from the start. Virtually any stable characteristic of a learner can be used as the basis for such informed decisions, provided the empirical data are available regarding how that characteristic is likely to impact learning in particular types of environments.

*Micro*adaptive instruction occurs *during* the training process. Microadaptation typically involves alterations in *what* is presented in the curriculum, as opposed to *how* it is presented. These decisions are made based on assessments of students' current states of knowledge and skills acquisition, compared with the level they should have achieved when training is complete. Where the student is lacking knowledge, the material is instructed, or perhaps it is instructed *again*. Material on which the student has an adequate level of expertise is either not instructed at all, or the student is allowed to move on past that information to a new part of the curriculum. Note that, like macroadaptation, microadaptation can be employed with groups of trainees, as well as with individuals.

These two instructional adaptation approaches can be used singly, together, or not at all in any given training effort. They are not inherently a part of either group or individualized instruction. However, one would expect to lose the potential benefits of individualized tutoring if the training were not tailored in some way to the characteristics of the learner. Instructional adaptations are also not necessarily part of a human tutor's training regimen, but most experienced human tutors perform both almost instinctively.

Three specific and interrelated streams of research have addressed the instructional adaptation issue: aptitude-treatment interactions (ATI), mastery learning (ML), and intelligent tutoring systems (ITS). The main idea underlying all three approaches is that teaching is best accomplished when instruction is tailored to individual learners, and each approach has empirical support indicating that carefully adapted instruction is superior to conventional instruction. The first of the three individualized training approaches to be discussed will be ATI research, which focuses on stable interindividual differences, and may be employed in the context of "macroadaptive modeling." This involves assessing students' knowledge and skill prior to training and relates to general, long-term aptitudes. The point of ATI research is to derive decisions about what kinds of learner aptitudes are better suited to which kinds of training environments. Next, we will define and discuss mastery learning. The presumption is that anyone can be elevated to "mastery" of some knowledge or skill given personalized instruction, where

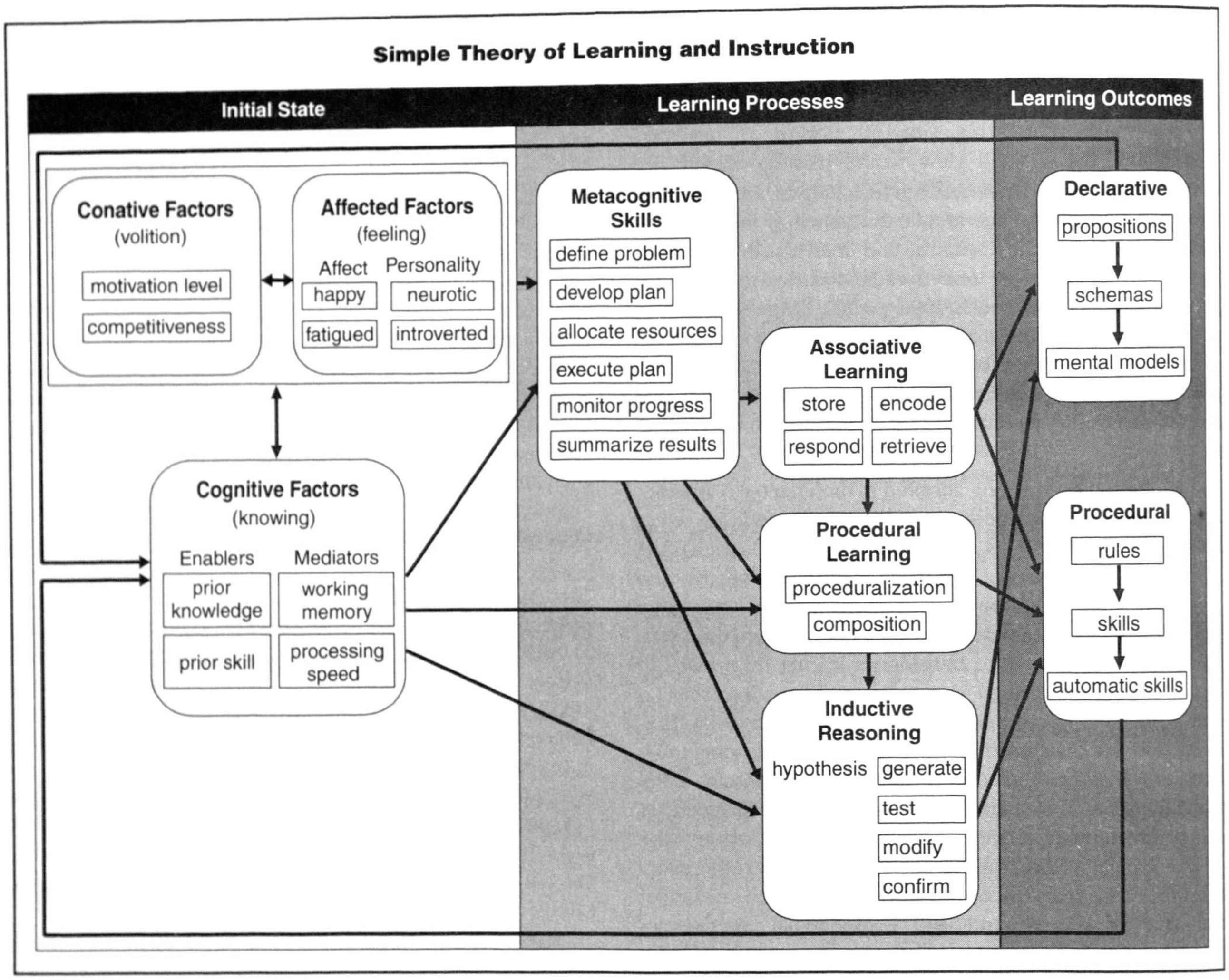

FIGURE 7-1

SOURCE: Adapted from "Learning processes and learning outcomes," by V. J. Shute, 1994, in T. Husen and T. N. Postlethwaite (Eds.), *International encyclopedia of education* (2nd Ed.) (pp. 3315-3325). New York: Pergamon.

instruction is dependent on one's individual response history demonstrated during the training session. Third, ITS research, like mastery learning, usually examines intraindividual differences, and these systems typically employ "microadaptive modeling" techniques. Microadaptive modeling focuses primarily on evolving student knowledge and skill acquisition that is specific to the task domain.

We deliberately covered approaches to adaptive instruction as a section separate from the discussion of individualized and group approaches, since ATI, ML, and ITS approaches can be applied in either setting. Additionally, it is possible to combine these approaches during group training. For instance, one could pull a particular trainee out of a small group to interact one-on-one with an ITS in order to hone a particular skill or expand a deficient knowledge base, then return him or her to the group as a more able learner and valued participant. Whether the specific application of these techniques is occurring at the group or individual level is determined by the level at which assessment and remediation take place.

APTITUDE-TREATMENT INTERACTIONS

ATI research reflects the notion that many kinds of learner characteristics (e.g., incoming knowledge, skills, and affective measures) affect what is learned in an instructional setting. The question of the optimal training environment for different kinds of persons is a classic aptitude-treatment interaction issue (Cronbach & Snow, 1977).

To employ ATI methods, one must make certain critical decisions. For instance, what aptitudes should be measured before training, which treatment variables should be manipulated, what learning indicators should be recorded to measure learning progress, and what learning outcome and efficiency measures should be used? The learning skills taxonomy developed by Kyllonen and Shute (1989) can assist in rendering principled answers to some of these questions. This taxonomy is defined by four dimensions: the subject matter, learning/training environment, desired knowledge outcome, and learner attributes. Interactions among these dimensions are believed to influence outcome performance, so that no single type of training environment is best for all persons. Rather, certain learner characteristics are better suited to specific kinds of environments to achieve optimal outcome performance (see Shute, 1992a, 1993a, 1993b, Shute & Glaser, 1990; Tobias, 1989, 1994). In addition, some domains lend themselves more readily to certain kinds of outcomes than to others. For instance, nonquantitative fields such as history emphasize propositions, whereas quantitative fields such as calculus focus on procedures. And finally, knowledge outcomes covary with instructional method: propositions are more commonly learned by rote and procedures are more commonly learned by practice (Kyllonen & Shute, 1989). We will now illustrate ATI findings from two studies, both of which resulted in decision rules concerning placement of various kinds of learners within different kinds of training environments.

ATI Example 1

The first study (Shute, 1993a) investigated learning from a flight engineering tutor and the potential impact of two different training environments (abbreviated versus extended practice conditions or few versus many practice problems) to solve per curriculum element. Approximately 370 subjects participated in the study, randomly assigned to one of the two practice conditions. All subjects were obtained from a temporary employment agency, and were paid for completing the study. None of the subjects had any formal training or experience with the subject matter instructed by the tutor. There was no main effect on learning outcome due to training environment, but a significant aptitude-treatment interaction was reported between an aptitude profile and treatment condition (see Figure 7-2). The aptitudes assessed within this study were measured with the CAM 4.0 battery of on-line cognitive ability tests (Kyllonen et al., 1990). These tests measure working-memory capacity, information-processing speed, inductive reasoning, associative learning, procedural learning, and general knowledge in verbal, quantitative, and spatial domains.

Subjects with a lot of general knowledge (GK) but low working-memory (WM) capacity learned significantly more if assigned to the abbreviated rather than the extended training condition. Their broad GK provided a foundation that allowed for the extraction and interweaving of information from relatively few exemplars, and their low WM capacities were not taxed within the abbreviated environment. However, these same subjects, assigned to the extended practice condition, performed poorly, probably due to boredom, fatigue, and/or working memory overload. The other type of subject was characterized by high WM and low GK. These subjects learned more from the extended than the abbreviated practice condition. That is, they had the capacity as well as the knowledge needed to profit from the extra practice afforded by the extended condition. The abbreviated condition appeared to be insufficient for these learners to learn the relevant principles. (Subjects who were characterized as being (1) high WM, high GK; and (2) low WM, low GK performed well and poorly on the

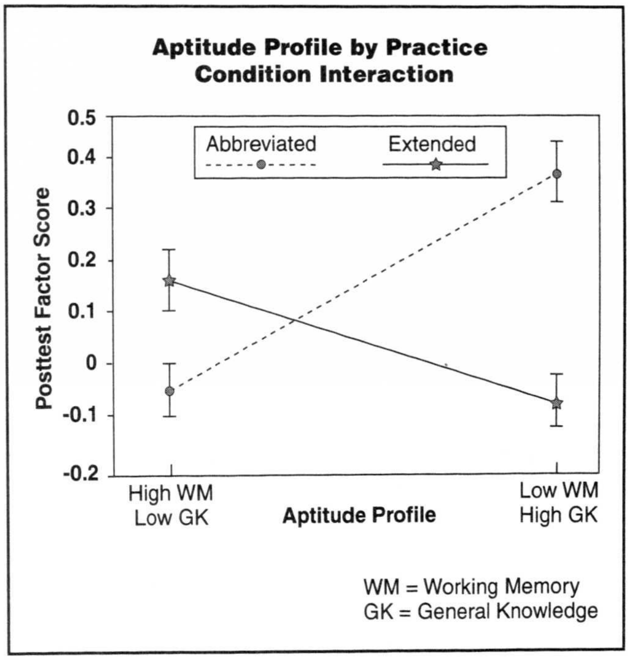

FIGURE 7-2

SOURCE: Adapted from "A macroadaptive approach to tutoring" by V. J. Shute, 1993, *Journal of Artificial Intelligence and Education*, 4(1), 61-93.

outcome measures, respectively, and regardless of treatment condition.) This finding suggests that individuals characterized by specific aptitude profiles are differentially suited to specific training environments. In practical terms, one use of the macroadaptive approach involves a priori assessment of learners' WM and GK, then subsequent placement into the appropriate environment. This type of modeling complements the more common *microadaptive* approach, which bases instructional choices only on student knowledge and performance within the training domain, and ignores information about students' more general abilities.

ATI Example 2

Swanson (1990) investigated an ATI that involved human tutors instructing a basic optics lesson on how lenses work. Two expert tutors taught identical curricula under three different treatment conditions: (1) discovery, where students were fully responsible for their own learning and were given only high-level verbal instruction and positive or negative feedback; (2) lecture, where the tutor controlled all instruction (similar to the instructional method still used in most schools); and (3) contingency, in which the degree of tutor involvement in the instructional process was contingent on the needs of each individual learner. Specifically, subjects were encouraged to do as much as possible on their own, but the tutor increased and decreased the level of control and intervention as necessary. In addition, there was a control, or baseline, condition involving no tutor; rather, learning was from a written text. The instructional content in this condition was identical to the three treatment conditions. The sample consisted of college students enrolled in an elementary algebra course, and their combined SAT scores served as the measure of aptitude.

Results from this study indicated a main effect of aptitude, but more relevant to the current discussion was a significant ATI (see Figure 7-3). In the discovery condition, outcome was highly predicted by ability level: low-ability subjects experienced great difficulty in that environment, while high-ability subjects performed at a much superior level. Subjects in the lecture condition showed the same trend, but not to such an extreme degree. Outcome differences between high- and low-ability learners were greatly attenuated in the contingency condition, where instruction was adapted to the needs of the individual students. The baseline group showed an interaction pattern similar to those learning from the lecture. Swanson (1990) concluded that her results provide further support for the advantages of adaptive instruction, and noted that ITS can provide a means of enabling teachers to create such environments in their classrooms.

Both of these ATI findings have implications for the design of adaptive training. Different types of individuals appear to perform better under different training conditions. That is, learning outcome is optimized when student characteristics are matched to treatment or training condition. In the first study, the explicit decision rule is: If learners have high working-memory capacity and low general knowledge, then place them in an extended training condition, otherwise the abbreviated condition is indicated. Trainers can avoid unnecessary time and effort in providing too many (or too few) practice opportunities by applying this decision rule. Such a policy would avoid investing too much of the trainees' time in surplus practice opportunities. Moreover, undue tedium during training almost certainly has other negative consequences as well, such as generalized loss of motivation, reduced time for other training needs, and increased attrition rates. In the second study, the decision rule can be reduced to the following: If learners are high ability, then place them in a discovery environment, otherwise place them in the more supportive (adaptive) contingent environment.

One way to take advantage of ATI methodologies and findings is to administer a battery of aptitude tests. For example, the Cognitive Abilities Measurement (CAM 4.0) battery (Kyllonen et al., 1990) is a collection of computerized tests measuring six different aptitudes (working-memory capacity, inductive reasoning skills, information processing speed, associative learning skills, procedural learning skills, and general knowledge) in each of three domains (quantitative, verbal, and spatial). In addition, computing a factor analysis on the test data produces a measure of general ability (or "g"), the first and strongest factor extracted. This particular battery has been widely tested and validated across thousands of subjects and multiple criteria. Furthermore, the test-retest and split-half reliabilities are both very high. Finally, individual tests can be extracted for different purposes and time frames. For instance, if you wanted to predict outcome performance on an air traffic control task, you could administer only a subset of the battery: tests assessing working-memory capacity and information-processing speed, within the spatial domain. We will now examine the second major approach to individualized training: mastery learning.

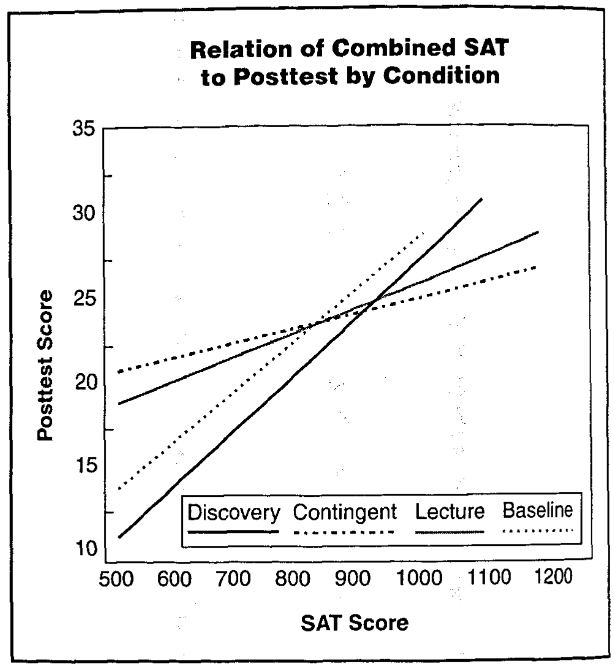

FIGURE 7-3
SOURCE: Adapted from *The effectiveness of tutorial strategies: An experimental evaluation*, by J. H. Swanson (1990, April). Paper presented the American Educational Research Association, Boston, MA.

MASTERY LEARNING

Mastery learning is the notion that, given clear instructional objectives, periodic diagnostic evaluations, and sufficient time, any learner can acquire the knowledge and skill being taught. The main defining characteristics of ML methods are "the establishment of a criterion level of performance held to represent 'mastery' of a given skill or concept, frequent assessment of student progress toward the mastery criterion, and provision of corrective instruction to enable students who do not initially meet the mastery criterion to do so on later parallel assessments" (Slavin, 1987, p. 175). Research into mastery learning took off in earnest in the late 1960s and continues today (Block, 1993; Bloom, 1968; Kulik, Kulik, & Bangert-Drowns, 1990; Stallings & Stipek, 1985). The basic idea underlying ML is that, though individuals *do* differ in terms of incoming knowledge and skills, if you permit everyone to learn at their own pace (i.e., allow instructional time to vary), then all can achieve mastery of educational and training objectives when achievement, or outcome, is held constant. This contrasts with typical pedagogy in traditional classrooms, which holds instructional time constant and allows achievement to vary.

Bloom (1984) identified problems associated with conventional teaching methods (e.g., a teacher presenting material in front of 30 people). He asserted that this format provides one of the *least* effective techniques for teaching and learning. As teaching becomes more focused and individualized, learning is enhanced. For example, when a teacher supplements a lecture with diagnostic tests to determine where students are having problems, then adjusts the lecture accordingly, this is called "mastery teaching." Bloom reported that students learning under this condition typically generate test results around the 84^{th} percentile, compared to test results around the 50^{th} percentile for those in conventional classroom settings. Furthermore, students involved in one-to-one tutoring with human tutors performed at around the 98^{th} percentile (2 standard deviation increase) as compared with traditionally trained students. Figure 7-4 shows these differences in outcome, with teacher-to-student ratios listed under each instructional approach. These results were replicated four times with three different age groups across two different domains. Bloom thus provides evidence that individualized tutoring can be an extremely effective educational delivery method. It was on the basis of these findings that Bloom issued his now famous "2-sigma challenge" to educators.

Slavin (1987) took issue with the claims made by Bloom (1984). In a comprehensive review of the ML literature, using a variation of meta-analysis called "best-evidence synthesis," he concluded that both the 2-standard deviation challenge and the 1-standard deviation claim for mastery approaches were "based on brief, small, artificial studies that provided additional instructional time to the experimental classes . . . [and the] 2-sigma challenge (or 1-sigma claim) is misleading, out of context and potentially damaging to educational research both within and outside of the mastery learning traditions" (Slavin, 1987, p. 207). In a follow-up, Slavin (1990b) responded to conclusions drawn from a large meta-analysis performed by Kulik et al. (1990). The key issue concerned the mixture of ML assessment measures that were used in the studies analyzed by Kulik et al. (1990). That is, if outcome is measured by a special test ("experimenter made"), and the curriculum differs between the experimental and control groups, then there will be a definite bias in favor of ML. On the other hand, employing an objective, standardized test provides a valid basis for making comparisons between different groups on the dependent measure, and shows no significant effects of ML.

In conclusion, while there is some debate over the *degree* of ML effects, the challenge remains. Mastery learning in general, and the 2-sigma challenge in particular, can serve as goals for researchers and practitioners in the quest to achieve the potential of ML methodologies in practical settings. We now examine the third major approach to individualized training: intelligent tutoring systems (ITS) (also see Chapter 16).

INTELLIGENT TUTORING SYSTEMS

ITS evolved from computer-assisted instruction (CAI) and computer-based training (CBT), both of which evolved from "intelligent" teaching machines (see Pressey, 1926; Shute & Psotka, 1996). An early outline of ITS requirements was presented by Hartley & Sleeman (1973), who argued that ITS must possess (1) knowledge of the domain (expert model), (2) knowledge of the learner (student model), and (3) knowledge of teaching or training strategies (tutor). It is interesting to note that this simple list has not changed in more than 20 years (see Lajoie & Derry, 1993; Polson & Richardson, 1988; Psotka, Massey, & Mutter, 1988; Regian & Shute, 1992b; Sleeman & Brown, 1982). All of this computer-resident knowledge of the curriculum, the learner, and teaching strategies marks a radical shift from earlier "knowledge-free" CAI/CBT routines (Shute & Psotka, 1996), which typically possessed neither the capacity for student diagnosis nor the ability to change the curriculum in response to that diagnosis. These abilities represent key differences between intelligent and non-intelligent computer-assisted training. Figure 7-5 illustrates these knowledge components and their relations within a generic ITS. Each of these ITS components will be discussed in turn.

A student learns from an ITS primarily by solving problems that are appropriately selected or tailor-made, and that serve as optimal learning experiences for that student. The system starts by assessing what the student already knows. This is called the *student model*. The system must also consider what the student needs to know; this information is embodied in the *curriculum* (also known as the domain expert). Finally, the system must decide what curriculum element (unit of instruction) ought to be instructed next and how it should be presented. This is achieved by the inherent teaching strategy, or *tutor*. From all of these considerations, the system selects or generates a problem, then either works out a solution to the problem (via the domain expert) or retrieves a prepared solution. The ITS then compares its solution, in real-time, to the one the student has prepared, and performs a diagnosis based on differences between the two. Feedback is offered by the ITS based on student adviser considerations such as how long it has been since feedback was last provided, whether the student already received some particular advice, and so on. After this, the program updates the student model, the record of what the student knows and does not know, incrementing any learning progress indicators. These updating activities modify the student model, and the entire cycle is repeated, starting with selecting or generating a new problem, or perhaps moving on to a new part of the curriculum.

Not all ITSs include these components, and it is possible to include other components as well. Moreover, the problem-test-feedback cycle does not adequately characterize all systems, but this generic depiction does describe the majority of current ITSs (see Goettl, Halff, Redfield, & Shute, 1998). Alternative implementations exist, representing conceptual as well as practical differences in design. For example, the standard approach to building a student model involves representing *emerging* knowledge and skills of the learner. The computer responds to updated observations with a modified curriculum that is minutely adjusted. Instruction, therefore, is very much dependent on individual response histories. But many have argued that incoming knowledge is the single most important determinant of subsequent learning (e.g., Alexander & Judy, 1988; Dochy, 1992; Glaser, 1984). Thus, an alternative approach to designing more responsive training involves assessing *incoming* knowledge and skills, either instead of, or in addition to, emerging knowledge and skills. This enables the curriculum to adapt to both persistent and/or momentary performance information as well as their interaction (see Shute, 1993a). Two examples of individualized training systems, along with associated evaluation results, are provided next.

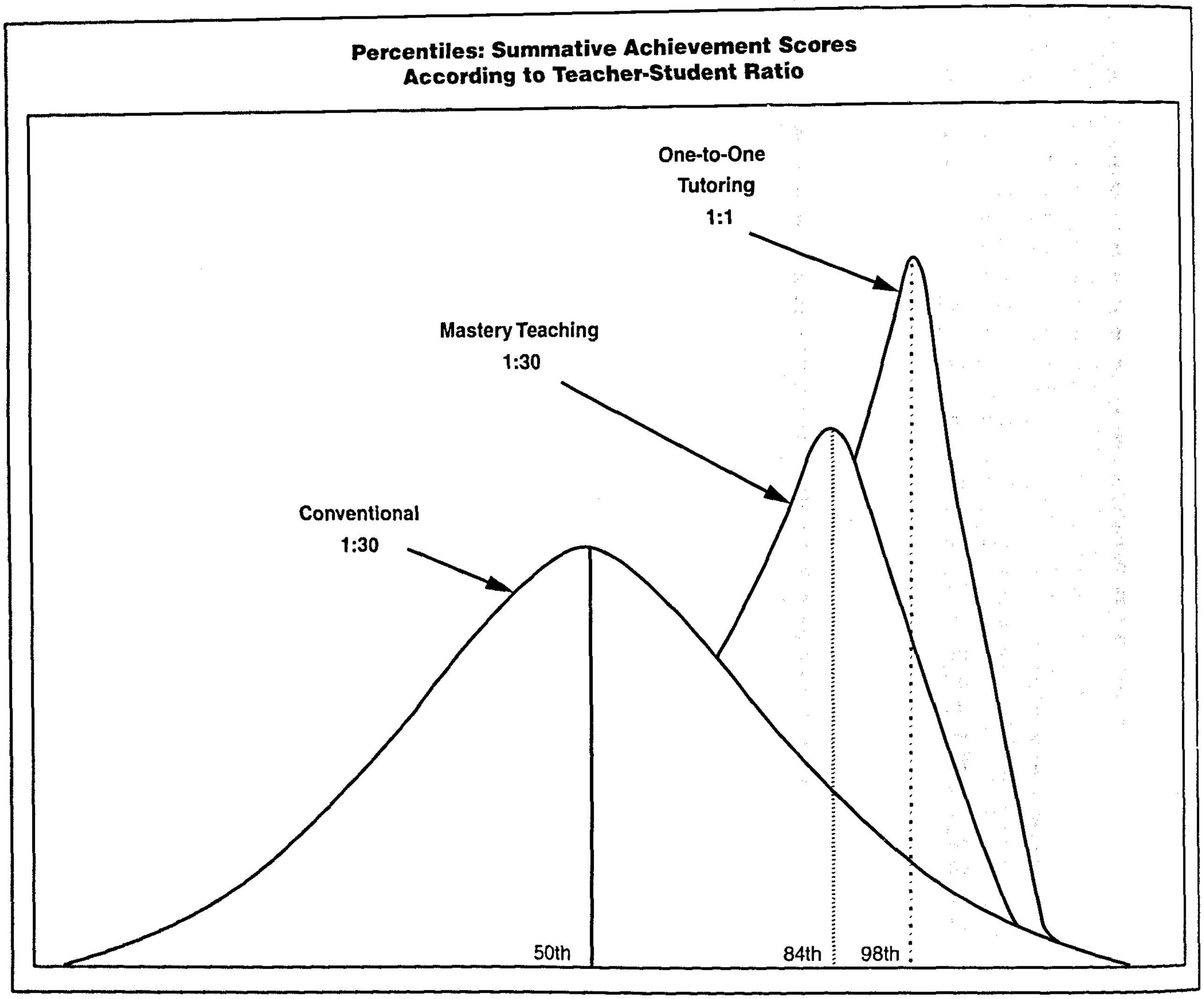

FIGURE 7-4
SOURCE: Adapted from "The 2-sigma problem: The search for methods of group instruction as effective as one-to-one tutoring" by B. S. Bloom (1984). *Educational Researcher*, 13(6), 4-16.

ITS Example 1

One of the longest-running and most successful ITS research groups is the Advanced Computer Tutoring Group at Carnegie Mellon. Since the early 1980s various members of that group have been developing, evaluating, and improving on intelligent tutors for computer programming, algebra, and geometry. Although the domains for which the ACT group develops tutors are clearly of the sort that would be covered in a high school or college education, the emphasis of their tutors is on procedural skill training. Therefore, their work seems germane to this chapter.

Anderson, Corbett, Koedinger, and Pelletier (1995) summarized the history of the work by this research group and the lessons they have learned. One of the tutors described in that paper is The Geometry Tutor (Anderson, Boyle, & Yost, 1985), which provides an environment for students to prove geometry theorems. The system monitors student performance and intervenes as soon as a mistake is made. The skill this system imparts is how to prove geometry theorems that someone else has provided, and the tutor has been shown to accelerate learning of the subject matter (Anderson et al., 1985) compared to control conditions. Schofield and Evans-Rhodes (1989) conducted a large-scale evaluation of the tutor in an urban high school. Six geometry classes were instructed by the computer tutor in conjunction with trained teachers, and three control classes learned geometry in the traditional manner. The researchers closely observed the classes for more than 100 hours. The vast majority of students within the treatment groups evidenced great interest in the material, contrasting with the control groups' moderate interest level as ascertained via post-learning interviews. Consequently, the treatment groups expended more time and cognitive effort in their learning sessions with the computer

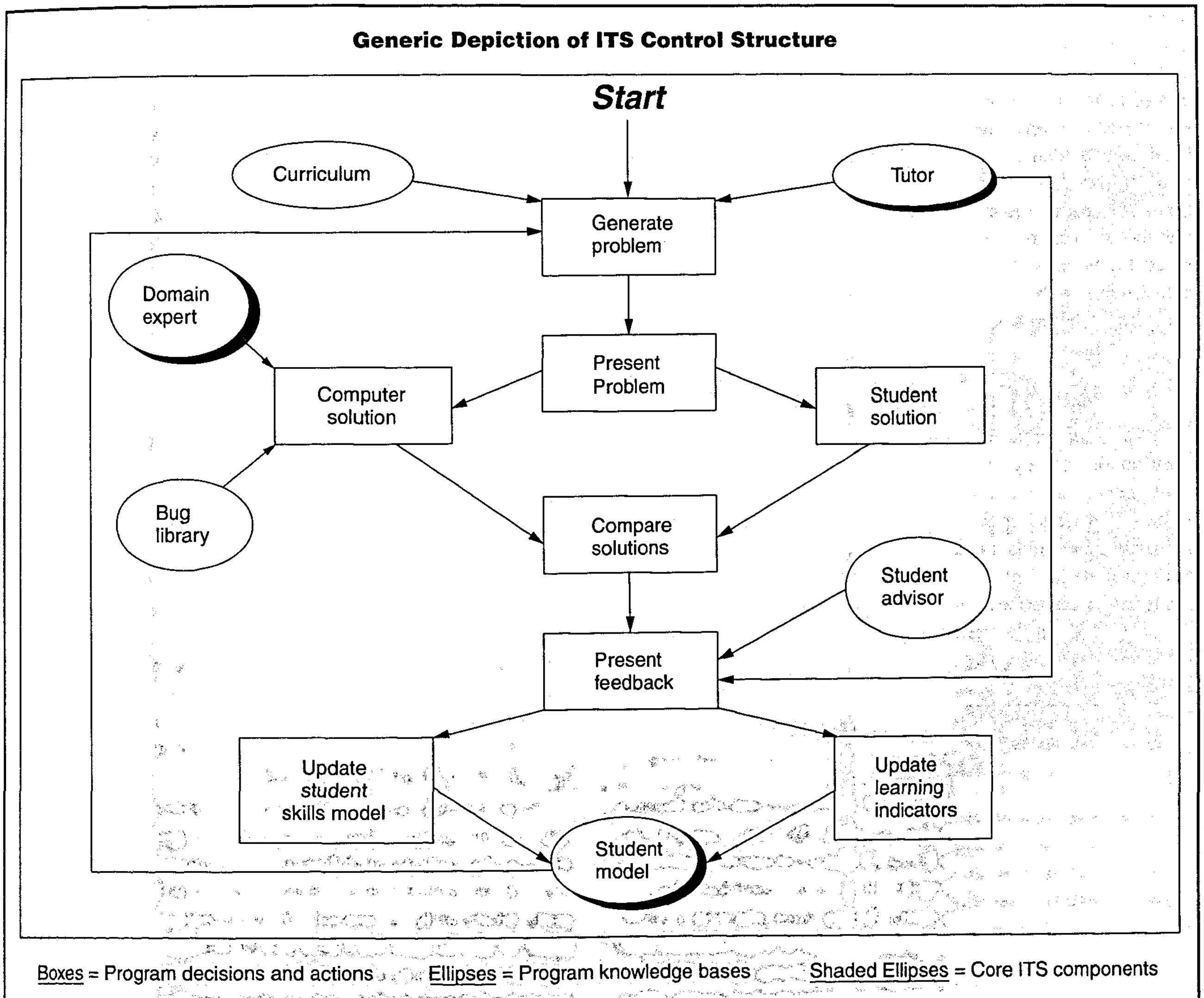

FIGURE 7-5

SOURCE: *Source:* Adapted from "Intelligent tutoring systems: Past, present, and future" by V. J. Shute and J. Psotka, 1996, in D. Jonassen (Ed.), *Handbook of research for educational communications and technology* (pp. 570-600). New York: Macmillan.

tutors. However, one of the most intriguing results of the Schofield and Evans-Rhodes evaluation was the counterintuitive reversal of its effects. Although The Geometry Tutor was designed to individualize instruction, one of its pragmatic and unintended side effects was to encourage students to share their experiences and cooperatively solve problems. Because their experiences with The Geometry Tutor were so carefully controlled by the immediate feedback principles of its operations, the tutor guaranteed that students' experiences were much more uniform and similar than those in traditional classrooms. As a result, students could more easily share experiences and make use of each other's experiences and problem-solving strategies. The practical result was a great deal of cooperative problem-solving that translated into significantly better outcome performances compared to those in the control condition.

ITS Example 2

Sherlock is the name of a tutor that provides a coached practice environment for training an electronics troubleshooting task (Lesgold, Lajoie, Bunzo, and Eggan, 1992). It serves as a stunning example of the increases in training efficiency that can be achieved when one moves from an inefficient training approach to the use of a well-designed ITS. The tutor teaches troubleshooting procedures for dealing with problems associated with an F-15 manual (not automatic) avionics test station. The curriculum consists of 34 troubleshooting scenarios with associated hints. A study was conducted evaluating Sherlock's effectiveness using 32 trainees from two separate Air Force bases (Nichols, Pokorny, Jones, Gott, & Alley, in preparation). Pre- and post-tutoring assessment was done using verbal troubleshooting techniques as well as a paper-and-pencil test groups of subjects per Air Force base were tested: one group of subjects received 20 hours of instruction on Sherlock, and a control group received on-the-job training over the same period of time. Statistical analyses indicated that there were no differences between the treatment and the control groups on the pre-test (means = 56.9 and 53.4, respectively). However, on the verbal post-test as well as the paper-and-pencil test, the treatment group (mean = 79.0) performed significantly better than the control group (mean = 58.9) and equivalent to experienced technicians having several *years* of on-the-job experience (mean = 82.2). That is, the average gain score for the group using Sherlock was equivalent to almost four years of experience.

The ATI, ML, and ITS approaches need not be viewed as mutually exclusive. It may be in fact more beneficial to combine micro- and macroadaptive modeling techniques in the personalization of training (Shute, 1995). Attending to both lower-level (micro) acquisition of knowledge and skills as well as higher-level (macro) characteristics of the learner means that instruction becomes more tailored to the individual. This is something that human tutors do automatically, or they at least can learn to do. Computers can be programmed to exhibit the same sort of flexible, adaptive behaviors.

INDIVIDUALIZED TRAINING

As the name implies, individualized training means to teach a single learner some knowledge or skill. Training may be delivered by a human instructor (e.g., tutor-to-student, master-to-apprentice) or computer program (e.g., computer-based training or intelligent tutoring system). It may take place in a classroom, laboratory, or workshop. Regardless of instructional medium or locale, in order to personalize training, it is critical to accurately assess, or "model," the learner/trainee in terms of his or her current state of knowledge and skill. That is, a valid determination should be made of what the learner knows (e.g., general aptitudes and domain-specific knowledge), to what degree, and what remains to be instructed or trained. This diagnostic process may generically be called student, or cognitive, modeling. A good teacher/trainer does this instinctively, and a good computer system does this by way of overlay models (i.e., comparing novice and expert solutions), heuristics, or probabilistic assessments. These techniques collectively characterize intraindividual differences in the learning process (individuals' progress through the training regime or curriculum). On the other hand, research examining interindividual differences provides information about knowledge and skills that influence outcome performance. Information derived from both of these research streams can be used to tailor training to the particular needs of a trainee within a specific domain, focusing on knowledge and skills known to impact learning outcome.

This section begins with a general overview of individual-differences research. Then we present three main approaches to individualized training, followed by a comparison of human- and computer-delivered instruction, evaluating the advantages and disadvantages of both methods.

INDIVIDUAL DIFFERENCES

Training is effective to the degree that trainees actually acquire the desired knowledge or skill. Thus, training issues are intimately tied to learning. During training, individuals differ significantly in terms of what they learn and how fast they learn it. From the time of Plato to the present, cognitive, conative, and affective factors have been considered major determinants of learning and performance (Ackerman & Kyllonen, 1991; Snow, 1992; Thurstone, 1947). In Snow's words: "Each person's mental bank contains not only bits and pieces of knowledge and skill, but also wishes, wants, needs, intentions, interests, attitudes, etc." (1992, pp. 28-29).

Cognitive

Cognitive factors are mental processes and structures associated with knowledge and skill acquisition, such as working-memory capacity and general knowledge (Anderson, 1983). Kyllonen and Christal (1989) differentiated factors into two main categories: "enablers" and "mediators" of learning. Enablers are what one already knows and can transfer to new situations (i.e., the depth, breadth, accessibility, and organization of knowledge possessed by a learner). Both the degree to which an individual's knowledge structure is well organized and the accessibility of the information in that framework affect the speed and accuracy with which *new* knowledge and skills are acquired and retrieved (see arrow in Figure 7-1 from cognitive factors to learning processes).

Prior knowledge (and especially *domain-specific* knowledge) is an enabler that has garnered a great deal of attention among the individual-differences community. Part of the reason for this is that domain-specific knowledge can be relatively straightforwardly assessed. A well-managed cognitive task analysis sheds light on the types of skills and knowledge units required by a particular task or set of activities, and this can be used to devise a valid and reliable pretest performance measure. One then has to simply administer the test to trainees to ascertain how much each one already knows about a particular topic or how well each trainee can perform a given task before training begins. Convenient assessment is not the only reason prior knowledge receives so much attention from the research community. It has also been found to be an extremely reliable predictor of depth, breadth, and efficiency of training (Tobias, 1989). Those who already have a declarative and procedural foundation on which to build when beginning to learn something new are likely to learn it faster, remember it longer, and transfer what they have learned to new situations (Chi, Glaser, & Rees, 1982; Shute, 1992b; White & Frederiksen, 1986).

Mediators represent *limits* on the maintenance, storage, and retrieval of information, thus governing the quality and rate of knowledge and skill acquisition. Some typical and powerful mediators include working-memory capacity, information-processing speed, inductive reasoning, general knowledge, associative learning, and procedural learning. Assessing these "hard-wired" cognitive abilities is more complex than measuring prior knowledge (see Kyllonen & Christal, 1989). Those interested in assessing these characteristics could spend years developing, evaluating/validating, and revising an acceptable battery of tests, but we recommend the use of a valid, reliable, preexisting

Adaptive Instruction

Summary Statements and Recommendations for Trainers

Adaptive Instruction	Human tutors tend to automatically adapt the content and delivery of a course of instruction to the needs and abilities of the trainees. One of the only instances in which this might not be the case would be if the tutor were delivering the material in a didactic lecture fashion. Tutoring via ITS should consider incorporating both macro- and microadaptive instructional changes, to minimize training time and optimize outcome. These adaptational decision rules should be derived minimally from well-established theoretical foundations, and ideally from the results of empirical research.
Aptitude-Treatment Interactions	ATI research has gone through a relatively checkered history of uncontrolled experimental designs, inconsistent results, and misinterpretation of conclusions. Despite these shortcomings, a careful review of the seminal research completed in this area demonstrates that ATI are ubiquitous in training, especially when cognitive ability and/or prior achievement serve as the basis for the aptitude portion of the interaction. Current research, conducted within the controlled environments offered by ITS, allows for more disciplined, direct tests of ATI. We recommend that trainers begin to look toward this growing body of empirical data to inform macroadaptive instructional decisions.
Mastery Learning	The ML approach to training leads to substantial increases in outcome, because therein lies the focus. Trainees must continue to study and practice until they reach a level of competence deemed acceptable by the tutor. This is in direct contrast to traditional classroom approaches, which hold instruction time constant, with little or no regard to individual differences in skills acquisition. We strongly recommend application of the ML approach to training whenever time constraints are flexible enough to make it possible.
Intelligent Tutoring Systems	ITS are effective instructional media to the extent that they are able to accurately assess trainees' incoming aptitudes, knowledge, and skills, diagnose deficiencies in performance during training, and use some or all of that information to tailor the learning experience appropriately. Objective evaluations of well-designed ITS have shown that they consistently allow for impressive knowledge and skill gains across widely disparate domains. Developers of ITS with training applications should be aware of existing cognitive psychology and ATI research results and use those data in designing their systems. In addition, they should allow for the possibility of taking a ML approach to interaction with the system, to maximize training outcome.

TABLE 7-1

cognitive battery, such as the Cognitive Abilities Measurement (CAM) battery, described earlier.

Conative

Conative factors are mental conditions (e.g., motivation, competitiveness) or behaviors directed toward some event (Kanfer, 1989). Learners need to focus their attention and persist in a new learning task, despite difficulties they may encounter, and conative attributes influence one's ability and/or willingness to persevere. Teachers have long known of the great influence of conative states on learning: For instance, students characterized as being anxious, depressed, or angry fail to learn as information is neither absorbed nor processed efficiently (Goleman, 1978).

Knowing a person's motivational state, in conjunction with his or her cognitive abilities, can enable one to predict learning outcome (e.g., Lepper, 1988). What influences intrinsic motivation? Cordova and Lepper (1996) discuss various factors, such as contextualization, personalization, and choice that affect motivational level. Lepper, Woolverton, Mumme, and Gurtner (1993) discuss expert human tutors and their allocation of at least as much time and attention to the achievement of affective and motivational goals as to the cognitive and informational goals typical of computer-based tutors. (See Vicente and Pain 1998 and Chapter 4 for a discussion of research and findings about motivation.)

Another heavily researched conative measure is *reflectivity impulsivity*, the tendency towards accuracy at the expense of speed, or vice-versa, in learning or problem-solving situations. Slower, more accurate, and thoughtful processing is equated with a *reflective* style, whereas faster, less accurate processing is associated with an *impulsive* style. Messer (1976) found a negative correlation between impulsivity and IQ, and when IQ was held constant, an inverse relationship still held between impulsivity and school performance. Impulsive individuals may not allocate sufficient time for processing information during learning, thereby negatively impacting outcome.

Lajoie & Shore (1986, 1987) found that the speed/accuracy tradeoff, as implied by the impulsivity/reflection literature, was not a given phenomenon when examining high-ability individuals. There were no significant differences in high-ability individuals who were slow and accurate (reflective), slow and inaccurate, fast and accurate, or fast and inaccurate (impulsive) (Lajoie & Shore, 1987). Furthermore, when examining the relative contributions of mental speed and accuracy to Primary Mental Abilities IQ measures were examined, both speed and accuracy independently predicted IQ but not speed over and above accuracy (Lajoie & Shore, 1986).

Interest is another conative attribute that influences learning (Tobias, 1994). Common sense dictates that those who are interested in training in a particular domain are also more likely to be motivated and attentive during the learning process; the result will be increased outcome. Moving beyond common sense, however, Schiefele, Krapp, and Winteler's (1992) meta-analysis concluded that interest accounts for 12 percent of achievement variance in males and 6 percent in females. Admittedly, that study focused on academic achievement rather than training success, but we contend that it serves as sufficient rationale for future research in this area. At the very least, interest and other conative variables hold promise for their incremental predictive power in accounting for training success, when used in conjunction with cognitive data.

Affective

Affective factors relate to feelings and personality (Ackerman & Kyllonen, 1991), like being happy, enthusiastic, conscientious, or neurotic. Individual differences in regard to conative factors are closely related to affective factors. To illustrate, if a person was unhappy and fatigued (two affective characteristics), then his or her motivation level (conative attribute) would most likely be depressed compared to that of someone else who was happy and alert, or even in relation to him/herself in a more elevated state. Consequently, learning processes, and hence, learning outcomes could be differentially affected by these affiliated states.

Cognitive factors tend to be more stable than conative variables, and both tend to be more stable than affective states, which are more transitory (for more on this topic, see Shute, 1994). In other words, cognition implies internal limits on learning, conation implies a preferred orientation towards learning, and affective states reflect environmental influences on learning that can be manipulated through instruction or other situational influences. In general, any "aspect of a person that can predict his or her response to instruction ought to be examined as relevant to important personal and instructional goals" (Snow, 1992, p. 9). Snow also mentions that we must exercise caution in reducing human learners to mere lists of variables and traits. Despite the fact that such reductionism is less than ideal, the current state of individual-differences research typically makes that approach unavoidable. Furthermore, the relatively simple method of categorizing learners along different variable and trait lines has often led to important advances in the field.

The "Initial State" column of Figure 7-1 represents three broad sources of individual differences among trainees. Although we do provide some specific examples to help instantiate this description, we have not attempted to furnish a comprehensive taxonomy of trainee characteristics or to elaborate on the many specific sub-characteristics within the realms of cognition, conation, and affect. For more in-depth coverage of these interesting topics, we recommend Snow's (1994) chapter on abilities, Ackerman and Kyllonen's (1991) chapter on cognitive characteristics of trainees, Kanfer's (1990) review of motivation and Chapter 4 (this volume), and Gough's (1983) review of temperament (personality/affect).

Learning *processes* may be globally defined as any series of mental actions directly responsible for learning outcomes. This definition encompasses a wide range of mental actions, differing in nature as well as scope of application. To organize and simplify the varied processes cited in the literature, Figure 7-1 shows four processing components, each with its own constituent processes. Three categories are arrayed along a dimension of increasing complexity, from basic associative learning processes (constructing simple relations) to procedural learning processes (constructing rules from the simpler relations) and ending with the more complex processes of inductive reasoning (organizing a coherent structure around the lower-level relationships). These three categories of learning are believed to be influenced by a fourth category, metacognition, which is personal knowledge of one's learning abilities and limitations, including skills that enable the acquisition and application of knowledge and skills. The specific processes included under this construct have been assembled from the voluminous research in this area (Baron, 1985; Brown, 1978; Collins & Stevens, 1982; Flavell, Friedricks, & Hoyt, 1970; Glaser & Bassok, 1989; Kanfer & Ackerman, 1989; Kuhl & Kraska, 1989; Schmeck, 1988).

Metacognitive processes monitor the efficacy of the three learning processes and, if necessary, invoke different processes during the solution of a particular problem. But the three learning processes (associative, procedural, and inductive) ultimately impact what is learned. An analogy can be made between a conductor and musicians performing during a symphony. A conductor directs the musicians, but does not actually play any music. The quality of the conducting affects the musicians, and thus the musical outcome. Thus, individual differences in the *application* of the processes constitute a major determinant of learning outcome.

The *outcome* of learning refers to any change within an individual's knowledge structure or skill level that results from training. Outcomes of learning can be quite diverse, differing in magnitude (e.g., learning a simple rule versus a complex technical skill) as well as content area (e.g., affective and social skills, motor skills, procedural knowledge). Figure 7-1 shows one way to characterize the assortment of learning outcomes. The declarative-procedural distinction is fundamental (declarative knowledge is knowledge *about* something, whereas procedural processes are the ability to *do* something), and refinements are possible within each of these two categories. That is, declarative knowledge and procedural skills can be arrayed by complexity. (For more on this topic, see Kyllonen & Shute, 1989; Shute, 1994.) Also, newly acquired knowledge and skill outcomes can be stored in long-term memory for use in *subsequent* acquisition of declarative knowledge or procedural skill, which would alter the content and structure of one's "initial state" and constitute a feedback loop between outcomes and initial states. Finally, a temporal element is involved in individual differences among abilities and processes; they are not static. Instead, aptitudes and learning processes are differentially important at various points in time across knowledge/skill acquisition. For instance, working-memory capacity and associative learning skills play an important role early in the learning process in determining the degree of new knowledge and skills acquisition. But over time, these become less important, and other factors gain importance, such as perceptual speed and perceptual/motor abilities (Ackerman, 1988, 1992; Woltz, 1988). This notion of a correlated time dimension has direct implications for developing adaptive instructional or training programs. Some skills may be taught early in the training program, and then the training focus can be switched to other critical skills once proficiency is achieved. Alternatively, intelligent instructional programs may adapt to individual differences in skill level. It may be beneficial, for instance, to switch instructional approaches during training, as changes occur in (1) the knowledge and skill levels of the trainees and (2) the cognitive requirements of the training regimen.

The main issues and approaches relevant to individualized training have now been outlined. Next, we discuss the advantages and disadvantages of the instructional medium in delivering training material, of human- versus computer-delivered training.

COMPARISON OF HUMAN- AND COMPUTER-DELIVERED TRAINING FOR INDIVIDUALS

As discussed above, significant advantages are associated with the individualized training approach, especially compared to traditional classroom instruction (Bloom, 1984). Though the "master and apprentice" approach to vocational training has existed for hundreds, perhaps even thousands, of years (see Chapters 2 and 11), only during the last several decades has the *process* of learning come under serious scrutiny in relation to individualized training environments. The question is not *whether* human tutors are effective, but rather *how* they are so effective. More specifically, what is it about the pedagogical strategies of experienced human tutors that makes it possible for them to train learners so effectively? Furthermore, how do these strategies compare with those employed by current ITS, and how can we create future ITS that are on par with, or even surpass, the tutorial efficacy of a human?

How Do Humans Do It?

The specific research approaches that have attempted an answer to this question represent variations on the same theme. Basically, the idea is to observe (and often, videotape) the entire interaction between teacher and pupil during the course of some pre-determined curriculum. This gives the researcher an opportunity to watch the tutorial interaction in real-time, and review the whole recording later to analyze the discourse at a more fine-grained level. In the most fundamental sense, one has information specifying what the two participants said to each other. However, this is just the tip of the iceberg. The wealth of data resulting from this investigative approach provides information about what was said, how and when it was said, and in what context (i.e., what the pupil and tutor were doing at the time) the communication took place.

Diagnosis. In this chapter, "diagnosis" and "student modeling" are used interchangeably, as both mean the process of making an assessment of the learner's current state of knowledge/skill, and use a variety of techniques to achieve this end. A more restrictive definition of "diagnosis" includes the ability to make inferences about why a learner performs in a certain manner. We prefer the less restrictive definition.

The human tutor's primary responsibility is to act as a diagnostician of the "state" (i.e., ability, interest, level of frustration, etc.) of the learner. If a tutor does not have a good understanding of the current knowledge state or ability level of the student, it is likely that the feedback or ensuing instruction will be inappropriate (e.g., improper type of problem or level of difficulty). The advantages of consistent and accurate diagnosis should be self-evident, but it may not be necessary to share this information explicitly with the learner. For instance, Merrill, Reiser, Ranney, and Trafton (1992) propose that instead of communicating their diagnoses to students, human tutors use that information as a basis for creating effective feedback and making any necessary curricular changes. The risk in sharing diagnoses lies in the potential for being wrong, thus diminishing the tutor's credibility.

Flexibility. Experienced human tutors possess the important ability to transform their "best-guess" diagnoses into real-time changes in the tutorial session. This is precisely where individualized tutoring achieves its great educational advantage over classroom instruction. By tailoring a session to meet the needs of a particular individual, the tutor is able to capitalize on that person's strengths and structure feedback and remediation around particular weaknesses. A sizable research effort has grown around the need to understand how, when, and why human tutors offer feedback about students' errors and misconceptions. Some researchers (Fox, 1991) have found that tutors will employ very indirect methods, like hints and leading questions, to allow students to discover errors on their own. Alternatively, McArthur, Stasz, and Zmuidzinas (1990) conducted a study in which human tutors used a very different approach. They not only identified students' errors as they occurred, but they also suggested new techniques for solving the problems.

Such a broad range of error-remediation behavior has prompted the generation of some initial conclusions about the varying factors that influence how a human tutor would react to different types of errors made in different contexts. For example, Littman (1991) and Littman, Pinto, and Soloway (1990) posit that an error's context and criticality (errors that demonstrated a poor understanding of previously-learned material are considered more critical) determine the content and timing of the feedback. For instance, there is often some inherent instructional benefit (and little potential harm) in making an error. An expert tutor who recognizes this may let a student continue to commit the error until he or she corrects the mistake independently, resulting in a deeper level of learning. Merrill, Reiser, and Landes (1992) were able to offer somewhat more specific rationales for various remediation behaviors by demonstrating that good human tutors quickly correct (1) errors that might be distracting or could lead to "floundering," and (2) problem components that are more seriously problematic. The errors chosen by the tutors for remediation are those that possess some inherent instructional benefit, so that individuals can learn from their mistakes.

Conclusions. The general finding is that experienced human tutors achieve a balance among the following: (1) allowing students to do as much of the work as possible, while (2) maintaining a sense of control over the learning process, and concurrently (3) providing students with sufficient guidance to avoid excessive feelings of frustration or confusion. This "balance" is truly fragile. A large body of research supports the importance of "learning by doing," positing that it is instructionally more effective to let students solve problems on their own, confront and work around obstacles, and then explain to themselves (and sometimes to others) what worked and what did not (Anderson, 1983; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Ohlsson & Rees, 1991; VanLehn, 1990). To give the student such a high degree of autonomy in the learning process, however, also means to run the risk of the student becoming upset, frustrated, and confused. Thus, "the assistance of a tutor enables a type of *guided learning by doing*, in which the students reap the rewards of active problem solving while the tutors minimize the dangers. In this way, tutoring has both cognitive and motivational advantages" (Merrill et al., 1992, p. 280).

How Do Computers Do It?

At the level of computer-based training (CBT) systems, designers specify the tutor's curricular goals (what it should teach) and decide on certain interface issues (what it will look like, what kinds of tools will be available to the user, whether students will use the keyboard or mouse, etc.) before beginning development. The end product is a "lock-step" series of instructional segments that proceed one after the other. These systems can teach certain knowledge and skills, and may differ in the degree to which they are interesting and challenging to the learner. A standard CBT does not diagnose the ability or affective states of the learner, and has a fairly inflexible curriculum. Therefore, everyone learning from that CBT is exposed to approximately the same thing (see Chapter 16).

Upgrading from a CBT system to an intelligent tutoring system (ITS) typically involves the addition of diagnostic and adaptive capacity. This is essentially an effort to make a computer program capable of modeling (diagnosing) the learner as accurately as an expert human tutor, and also to give the program the "intelligence" necessary to use that information in adapting instruction. As a detailed description of the framework of a generic ITS has already been covered, the salient issue now is: How do current ITS fall short of their goal? In what ways are their capacities inferior to those of human tutors?

Shortcomings of ITS. One salient difference concerns flexibility in both the curriculum and error remediation process. The strategy for responding to errors is fixed in most current ITS, whereas human tutors strategically moderate their responses, sometimes intervening immediately and other times letting the student wander down the wrong path for a while, depending on potential instructional value. A related difference has to do with flexibility in terms of presenting the curriculum. "Human tutors clearly adapt the curriculum for pedagogical advantage" (Merrill et al., 1992, p. 299), maximizing learning efficiency and outcome. Adaptation at that level is rare, if it exists at all, even in some of the most advanced ITS available.

A second major difference between human and computer tutors is that feedback from the human tutor tends to include fewer of the specific components of the error recovery process, thereby making the student responsible for most of the problem-solving effort. Most ITS researchers, however, have spent considerable time and effort on designing feedback that is so detailed and directive that it even relays diagnostic information to the learner (see Clancey, 1986, for a review). This is true despite evidence that human tutors typically do not provide diagnoses (Lepper & Chabay, 1988; Merrill et al., 1992; Putnam, 1987). Furthermore, it has been reported that explicitly providing diagnostic information does *not* improve students' performance more than simply leading the students through the correct procedure over again (Sleeman, Kelly, Martinak, Ward, & Moore, 1989). Thus, designers of ITS may attain more effective systems if the focus is shifted *away* from methods that attempt to convey diagnostic information to learners, and *toward* attempts to mimic and improve on the various ways human tutors actually use their diagnoses in structuring feedback.

Finally, owing to the wide array of communication avenues that can exist between two people—verbal information (including intonation), facial expressions, eye contact, body language, etc.—human tutors are capable of feedback that is substantially more subtle than that which occurs within existing ITS. The extraordinary subtlety of the feedback provided by the tutors in Fox's (1991) study, for example, is evident in the finding that even a very brief hesitation (often less than one second) in supplying positive feedback indicated to students that something was wrong with the step they had just taken. Students then usually found and corrected the mistake. Thus, communication between a human tutor and student is both highly interactive and often quite subtle.

Advantages of ITS. Despite the many shortcomings of present-day ITS, computerized tutorial environments do offer definite advantages over human tutors. Humans have limited working-memory capacity, but computers do not. For instance, they would not "forget" to cover a topic or emphasize a point (as long as they are programmed correctly). Furthermore, computers do not have any "patience" or "tempers" to lose, as humans sometimes do. A learner can struggle all day with a particular problem, and the computer will continue to reteach and offer feedback and encouragement. Another important advantage of computers over human instructors is that they are not prone to subjective influences: they do not "play favorites" or have "pets." Every learner is special. Finally, computers are invariably attentive. You are not likely to find one ignoring you while it attends to the needs of others.

How Could Computers Do It Better?

Despite these demonstrated advantages, there are numerous research opportunities for those looking for ways to enhance the tutorial capabilities of ITSs. This research is going on all over the world, at academic institutions, in private industry, and on military bases. For example, Moore (1994) and her colleagues at the University of Pittsburgh examined different ways to make ITS feedback more natural. On the basis of their study of human-human reflective dialogs, they are developing a taxonomy for types of contextual effects that occur in their data according to the explanatory functions they serve. So far, they have identified four main categories: (1) explicit reference to a previous explanation (or portion of one) in order to highlight similarities and differences; (2) omission of previously-explained material to avoid distraction from what is new; (3) explicit marking of repeated material to distinguish it from new material; and (4) elaboration of previous material in the form of generalizations, detail, or justifications. They have already made progress toward building a system that takes prior utterances into account when planning explanations.

Another area of research involves enhancing student models to make them more adaptive and, hence, effective. To illustrate, SMART (Student Modeling Approach for Responsive Tutoring, Shute, 1995) represents a type of student modeling that is both broad and powerful, and operates by applying a series of regression equations to learners' actions to predict knowledge and skill level. The resulting diagnosis determines the tutorial action, or curricular flow, for a particular learner, such as receiving instruction on a new section of the curriculum, remedial instruction on a problematic element, or continuing to solve problems that embody a set of related curricular elements. SMART not only models *evolving* knowledge and skills (domain specific) for purposes of microadaptation, it assesses *incoming* abilities (general and specific cognitive aptitudes) as predictors of subsequent learning and indicators of suitable instructional environments for macroadaptation. Moreover, whereas most other approaches focus on single outcome types (e.g., model tracing for procedural skill acquisition), SMART models a range of outcome types, including: symbolic knowledge (SK), procedural skill (PS), and conceptual knowledge (CK).

SMART has been incorporated into an experiential learning environment called Stat Lady (Shute & Gluck, 1994) and is currently undergoing a series of controlled evaluation studies where the main components (diagnostic updating routines and mastery/remediation control structures) are being systematically evaluated. Two studies have recently been completed and are discussed in more detail in Shute (1995). Results show dramatic (2.2 standard deviations) learning gains in the normal Stat Lady environment and even greater improvement with SMART actively selecting the curriculum.

GROUP TRAINING

Individualized training can often be quite resource-intensive. A more economical alternative is group training. The presumption underlying group training is that students/trainees working together in groups can learn more than or at least as much as they can by themselves, especially when they bring complementary rather than identical contributions to the joint enterprise (Cumming & Self, 1989). Group training approaches may serve to enhance learning by providing an avenue for conversations with other people who have differing opinions, backgrounds, or skills; who know more about some topic; or who can ask perceptive, thought-provoking questions. Two basic questions relevant to this section are: (1) Under what conditions are two (or more) heads better than one? (2) Can computer systems support collaborative learning endeavors as well as humans? Recent research is beginning to shed light on both of these questions. Many researchers have shown impressive student gains in knowledge and skill acquisition from collaborative learning environments (Brown & Palincsar, 1989; Lampert, 1986; Palincsar & Brown, 1984; Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989; Schoenfeld, 1985). Furthermore, several studies investigating the effectiveness of collaborative learning from computer-based environments have also been positive (Justen, Waldrop, & Adams, 1990; Katz & Lesgold, 1993; Papert, 1980).

We will begin this portion of the chapter with a look at a popular technique sometimes used in academic, industrial, and military settings for training large groups of people simultaneously: the workshop. We argue that one should be cautious in relying too heavily on workshops for training, as they are rarely subjected to objective, evaluative study. Then we distinguish among some of the main types of small-group training environments (collaborative, cooperative, and competitive), and discuss three separate approaches to small-group training (social constructivism, cognitive apprenticeship, and situated learning). Following that, we examine some of the variables that impact group dynamics, such as gender and aptitude, and conclude this section with a review of some current computer systems that have been designed for small-group learning, showing the strengths and problems associated with this endeavor.

LARGE-GROUP TRAINING

Seminars, conferences, and workshops have become very popular large-group instructional approaches. These three terms are often used interchangeably, but one particular characteristic of the workshop separates it from its counterparts. Mayo and DuBois (1987) note that the overarching purpose of a workshop is generally to aid trainees in the acquisition of skill(s), whereas seminars and conferences have a more theoretical, conceptual, knowledge-based orientation. Given that we defined training earlier as being more on the skill end of the knowledge-skill instructional continuum, we will focus only the workshop approach to large-group training here.

Workshops

Generally speaking, all workshops are designed in response to a perceived need for skills training in some area. They may require anywhere from one or two hours up to two full days for completion, as dictated by the nature and number of skills being taught, but are usually not longer than that. Workshops typically begin with a relatively formal introduction of the goals and content of the workshop, followed by a demonstration of the skill to be imparted. Participants then work individually or in small-groups to facilitate acquisition. During this period, the tutor/leader circulates among the groups, reviewing their efforts and offering constructive commentary (Jaques, 1992). Finally, everyone reconvenes in the large group to share experiences, show products, ask questions, and close the session. This pattern sometimes repeats itself several times within the same workshop.

Workshop participants are assumed to be persons who have

Individualized Training

Summary Statements and Recommendations for Trainers

	Individual Differences
Cognitive Factors	Cognitive factors (both general cognitive ability and more specific variables like prior knowledge, working memory, or academic achievement) can and should be used to predict training success, in terms of depth, breadth, efficiency, retention, and transfer. This general conclusion remains true across virtually all domains, and those interested in improving the training process are remiss in ignoring them. We recommend that trainers administer either a single test or a battery of tests before instruction and then use those data to make pedagogically appropriate decisions before and during training.
Conative and Affective Factors	These variables do not account for as much success in training as cognitive components. Conative and affective data may be valuable, however, from the standpoint of incremental predictive validity (when used in conjunction with cognitive information). These variables are also important to consider during the design of instruction, regardless of approach taken (e.g., experiential learning opportunities render learning more motivating and hence memorable so should be included in the interface between learner and learning environment).
Summary	*Looking back at Figure 7-1, the trainee's initial states influence learning processes (associative, procedural, and inductive), and the learning processes impact what the trainee ultimately acquires during instruction.*
	Human- and Computer-Based Training
Human Tutors	The most advanced ITS available are not nearly as sensitive to the many verbal and nonverbal communication paths that relay information about a trainee's learning experience, even when compared to many novice human tutors. Current ITS are also generally not as flexible as human tutors in terms of pedagogical, curricular, and remediational decisions, as ITS are constrained by the approach(es) implemented within their design. Nevertheless, interactions with ITS tend to result in significant knowledge and skill acquisition, and can be a very cost effective way to train large numbers of people. In addition, ITS make it possible to avoid some of the pitfalls inherent in human tutoring, such as forgetting to emphasize an important point, loss of patience, and divided attention.
Intelligent Tutoring Systems	Although the skill and knowledge improvements evidenced by trainees working on ITS are generally significant and encouraging, ITS are unlikely to raise trainee performance to the level achieved by human tutors. We suspect that this is primarily due to the still limited diagnostic capacities of modern computer systems, as well as a deficient theory of pedagogy. From a purely practical point of view, if the decision has been made that individualized tutoring is the approach needed, trainers should probably employ human tutors, unless the cost efficiency of the ITS approach (as a function of the number of trainees involved) warrants accepting slightly inferior outcome scores. As psychologists interested in this pursuit, however, we selfishly hope that more people become involved in continuing basic and applied research on improvements and refinements in the areas in which ITS have inferior capabilities, so that they may begin to more closely approximate true intelligence.
Summary	*Individualized human tutoring achieves such extraordinary results primarily due to the tutor's finely-honed ability to diagnose a trainee's strengths and weaknesses, and then tailor the ensuing instruction, feedback, and remediation appropriately. Human tutors employ a diverse array of error recovery, feedback, and remediation techniques in tailoring instruction, taking into account characteristics of the learner, the domain, and the training environment, the context and criticality of errors that are made, and how the learner has responded to various interventions in the past. Computer tutors, while not yet at the same level as humans regarding these abilities, offer some advantages over humans (see above), and the field of automated instruction is still in its infancy.*

TABLE 7-2

an immediate use for whatever skill(s) will be instructed, and so issues of motivation and interest are generally not a concern. In fact, Mayo and DuBois (1987) suggest that "it is best not to encourage individuals who do not have an immediate need for the skill to attend a workshop. Such individuals tend to view the workshop as a waste of time and as irrelevant to their job assignments or interests" (p. 77). Since workshops are intentionally designed to impart very specific skills, one must be careful to confirm beforehand that the goals of the workshop trainer match those of the trainee. Along the same lines, we caution the use of workshops for training purposes. One should not commit to a training workshop under the naive assumption that the leader has developed the curriculum and pedagogy with careful regard to the latest empirical research results, or that the techniques and materials to be used are valid and that the workshop itself has undergone rigorous evaluative development. Though the more effective and efficient workshops will likely be properly developed, we know from our own personal experiences and from those of our friends and colleagues that the workshop approach often simply does not manage to impart a level of skill consistent with the needs and expectations of the participants. This could be due to any number of factors (e.g., lack of preparation on the part of the workshop leader, mismatch between training objectives and the particular pedagogy employed), but one issue that is especially striking is what we perceive to be a general lack of evaluation.

Assessments of the short- and long-term performance improvements by workshop attendees, as well as evaluations of the degree of actual skill transfer from the workshop to novel workplace environments are, for the most part, nonexistent. We encourage those considering the workshop as a training alternative to be aware of this and to inquire about any existing evaluations of a workshop before committing to it. On the other hand, if the design of the workshop appears to have a strong foundation in theory and empirical research, as well as positive evaluation results, then it may be a cost-effective means to learn or hone a skill.

It is hardly coincidental that even within a broadly used "large-group" training approach like the workshop, there is such a strong focus on breaking the group down into smaller study, practice, and discussion groups. Rather, this reflects a growing realization of the instructional power of the small-group, which is where we now turn our attention.

SMALL-GROUP TRAINING

Some researchers who examine small-group learning phenomena use the terms "collaboration" and "cooperation" interchangeably (Noreen Webb, personal communication, February 1995). However, we have chosen to make a distinction between these two kinds of small-group training environments. *Collaboration* is defined as a process by which "individuals negotiate and share meanings relevant to the problem-solving task at hand" (Teasley & Roschelle, 1993, p. 229). This is distinct from *cooperation*, which involves the division of labor required to achieve some task. We also review a third small-group approach to training, *competition*, where the focus is more on competing against rather than working with others in a small group.

Interaction in Small-Groups

Collaborative Learning. *Collaborative learning* refers to small-group learning situations where individuals are encouraged to share their knowledge and skills with their peers as they work together on a common task or in a shared learning/training environment. Proponents of this approach make the case that collaborative learning has numerous cognitive, social, and motivational benefits, including greater learning, improved productivity, increased time spent on task, higher motivation, and heightened sense of competence (Johnson & Johnson, 1989; Rysavy & Sales, 1991; Sharan, 1980; Slavin, 1990a, 1990b). Ideally, collaborative group work provides opportunities for exposure to multiple points of view, thereby allowing learners to consider issues that would not have emerged had they been working independently. The hope is that when students construct and communicate their thoughts verbally, group problem-solving activities will encourage learners to explain, justify, and negotiate meanings, strategies, and skills. Small-groups can thus provide the means for greater communication and the development of higher-order thinking skills such as problem solving and inductive reasoning (Lajoie, 1991). In addition, collaborative learning typically results in increased persistence within a problem-solving task, consideration of alternative problem-solving strategies, peer feedback, and the application of a learned strategy in other situations (Duren & Cherrington, 1992). Although peer collaboration is more effective than individualized training for making shifts in perspective, the mere presence of a peer is not sufficient for effective learning. Joint decision making, on the other hand, *is* a necessary component of collaborative learning (Rogoff, 1991).

Another stream of research, reported by Greer et al. (1998), describes the researchers' efforts in developing peer help systems for university students. This consists of "help resources" at both the institutional and the course level. The two programs discussed in their paper provide tools for students helping students, either electronically or in person. This is accomplished by modeling the student knowledge of the person requesting assistance and also the relevant subject matter.

There are some potential problems associated with collaborative learning. Work that is conducted collaboratively can sometimes result in a reliance of some members on other members of the group, which may (1) reduce personal responsibility and (2) decrease independent thinking (Blumenfeld, Soloway, Marx, Krajcik, Guzdial, & Palincsar, 1991; Corno & Mandinach, 1983). One must therefore be careful in the implementation and execution of a collaborative learning situation.

Cooperative Learning. *Cooperative learning* occurs in a situation where a group of students or trainees is faced with a complex problem-solving or learning task that requires each of them to take responsibility for some subunit of the larger activity and work on it separately. Students then come together in the group to discuss their findings. Though this is often a more efficient group approach than collaborative learning, it sometimes results in less interaction among members of the group. Despite this problem, several studies have reported that students working cooperatively in small-groups produce equal or higher achievement than students working alone (Johnson & Johnson, 1989; Warring, Johnson, Maruyama, & Johnson, 1985; Yager, Johnson, & Johnson, 1985). The optimal size of the collaborative group appears to be two or three individuals (Cox & Berger, 1985; Webb, 1987). Recent CBT research also supports this contention that cooperative, small-group environments, especially dyads or triads, yield greater achievement than individualized training (Carrier & Sales, 1987; Dalton, 1990; Johnson, Johnson, & Stanne, 1985; Shull, 1990; Stephenson, 1992). The effects of this type of training condition on outcome measures (especially in respect to the subtasks that students did *not* complete themselves), offers an area rich with research possibilities.

Competitive Learning. In competitive learning, individuals within or between groups compete with each other to produce superior performance. The two most common forms of this type of environment are (1) military training settings using simulators to create various military scenarios that require trainees to practice tactics and strategies against each other and (2) entertainment settings, where video action games provide the forum for players to compete against each other (typically on a network) within artificial worlds. Though competition has been employed with varying degrees of success within educational settings, we will not review that literature in this chapter (see Johnson & Johnson, 1975, 1989, for more extensive coverage of this topic).

The best-known example of a competitive training environment is SIMNET, a group of simulators in common use throughout the Army for both training and development work. SIMNET stands for "simulation network," and represents a joint DARPA/Army program for demonstrating local and large scale networking of military based weapons simulators. This program, in operation since the early 1990s, makes it possible to conduct regular and intensive practice of combat skills by numerous large military teams in widespread locations. In addition, it provides the capability to conduct evaluations of new, emerging tactics, doctrine, and weapons systems. Preliminary insight based on the SIMNET experience (Psotka, 1993) provides both personal testimonials to the motivating and stimulating effects of the social and vehicle-based immersion of synthetic environments, and preliminary effectiveness data on its potency for learning and training. Even though SIMNET provides an impoverished perceptual simulation of a tank in action, the cues from active social engagement of crew members' communications, as well as the auditory and visual cues of the simulated sights, provide believability. Moreover, the evidence clearly shows training effectiveness (even without a curriculum) that is superior to many other classroom and simulation-based efforts (Bessemer, 1991). Research is continuing to assess how to make this training more effective by including surrogate crew members and intelligent semiautomated forces in the environments. The need to involve infantry, not just tanks and vehicles, is creating a research base for better computational models of agents and coaches (Badler, Phillips, & Webber, 1992).

Three Specific Group-Learning Approaches

Current theories of learning and training are increasingly centered on the learning process as it occurs within "situations," or meaningful contexts (Brown, Collins, & Duguid, 1989; Collins, Brown, & Newman, 1989; Eisner, 1993; Greeno, 1989; Resnick, 1987; Shuell, 1993). Often in both the laboratory and the "real world," these situations consist of small-groups of individuals working together on a common task, either collaboratively or cooperatively (for more on team training, see Chapter 12). Thus, group training must be considered within these new theories or frameworks for learning. For instance, constructivist (Vygotsky, 1978) and situated learning theories (Greeno, 1989, 1998) emphasize the importance of social interactions for promoting thinking and the development of problem solving skills. The assumption is that learning is enhanced when one shares cognitions with capable peers (Vygotsky, 1978). According to Collins et al. (1989), these shared cognitions liberate knowledge from specific contexts and encourage transfer to new problems and new domains. When learning takes place in "psychologically safe" learning environments, individuals can learn from each other's mistakes and reduce their own anxiety (Duren & Cherrington, 1992). Similarly, cognitive apprenticeship models of instruction (see Collins et al., 1989) suggest that small-group learning situations provide opportunities for learners to see others at various stages of development, thus providing benchmarks for learners' progress, resulting in the observation that learning is an incremental process. Social constructivism, cognitive apprenticeship models, and situated learning theories all have potential applications in both individualized and group training environments. The examples used here are all cases where they are employed in small-group training, so the theory and research results from each will be reviewed in this section.

Social Constructivism. The theoretical basis of this approach is that learning is a social activity, actively constructed during the process of sharing cognition with others (Vygotsky, 1978). Part of this sharing process involves recognizing and resolving cognitive conflicts that are embedded in social situations where opposing viewpoints are voiced (Doise & Mugny, 1984; Piaget, 1932). Because learning takes place in a social context, learners interact with and internalize modes of thinking and knowing with others (Toulmin, 1972). In fact, "our daily lives are filled with instances in which we influence each other's constructive processes by providing information, pointing things out to one another, asking questions, and arguing with and elaborating on each other's ideas" (Resnick, 1991, p. 2). Other literature supports the notion that students learn more by articulating their knowledge to others, particularly during self-explanation (Chi & VanLehn, 1991). When situating instruction in meaningful contexts, the social group is part of that context.

The social constructivist theory has found support in many subject-matter domains, such as reading, writing, and mathematics, as well as in the professions, such as medicine, law, and avionics. A few examples of knowledge construction in group situations are subsequently provided.

Mathematics. Recently, several researchers have been examining the construction of mathematical meaning using small-group environments (e.g., Cobb, Wood, & Yackel, 1990; Lampert, 1990; Resnick, 1988; Schoenfeld, 1985). The group facilitates reasoning about mathematics and can also foster reflection or metacognitive skills necessary to evaluate mathematical problems (Schoenfeld, 1985). Lampert (1990) discusses the importance of finding a common mathematical language for learners to use when communicating ideas, since language facilitates learning in social situations. One goal of this research is to determine effective ways to foster dialogs among participants. Dialogs are important for facilitating access to multiple, as opposed to single, problem representations (Resnick, 1988). Part of this communication involves group discussion of problem representations that can be argued *before* mathematical procedures are employed. Resnick has been particularly clear on the necessity of having a common core of knowledge in order to promote the types of dialogs that Lampert refers to in her work.

Law. In law, a prevailing form of instruction is the "case method." Students individually read assigned legal cases and prepare summaries that they present to the class. The professor typically asks questions about the student summaries to ensure that each case is completely covered. One goal of the case method is to allow students opportunities to actively explore problems with help from the professor (Harno, 1953). In principle, this seems conducive to the social constructivist philosophy whereby individuals learn from the multiple perspectives in the class. In practice, however, it appears that only a handful of students participate in the ensuing discussions (Cavers, 1943; Stevens, 1973). More recently, Williams (1992) has examined this instructional/training process within natural settings and found, similarly, that not all students are active in the case method. Consequently, the conclusion that everyone learns the same things from case presentations is erroneous (see also Bryden, 1984; Ogden, 1984; Chapter 17).

Medicine. Medical students also engage in problem-based learning situations. They work in small tutorial groups to diagnose patients' problems and understand the causes. Williams (1992) suggests that a more guided approach is necessary in both the case-based and problem-based learning situations to ensure the benefits of the social constructivist model. She suggests that the frustration of trial-and-error learning could be reduced if an approach were developed to model expert problem solving in these areas. These models should include examples from the entire problem-solving cycle, such as planning, executing, evaluating, and revising all of the various potential solutions. (See Chapter 17 for further discussion.)

Avionics. Katz and Lesgold (1993) have investigated how a computer tutor can be designed to facilitate learning in collaborative learning situations for teaching avionics troubleshooting. This approach embodies the social constructivist theory as the small-group learning situations are assisted by computers, which support the review of expert and novice problem-solving traces. Katz and Lesgold have linked the benefits of a computer tutor with the human resources of the small group, which can provide explanations in the context of problem solving. They accomplish this goal by using the computer to *foster* group discussions and by critiquing problem-solving performances. The opportunity for learning through peer negotiation is scaffolded by the computer's coach module, which generates expert feedback on the group's hypotheses or troubleshooting plans. (The term "scaffolding" is a metaphor for the construction of knowledge. The computer provides a scaffold for learning by offering helpful feedback, directed questioning, reminders, and suggestions for discussions with other learners.)

The same caveats that apply to cooperative learning situations also apply to the application of the social constructivist theory. Namely, not all peer-learning situations are successful (Johnson & Johnson, 1985; Slavin, 1985, 1990b). The effectiveness of small-group training environments depends on the nature of the task, abilities represented by each member in the group, and individuals' abilities to monitor their own understanding and compare their views with those of other group members (Blumenfeld et al., 1991). Social experiences can dramatically shape an individual's interpretations (Mead, 1934), and the main goal of training is to make those interpretations (or knowledge and skill constructions) as valid as possible.

Cognitive Apprenticeship. The cognitive apprenticeship model (Collins et al., 1989) is an attempt to anchor instruction within meaningful situations where the learning of knowledge and skills becomes embedded in the social and functional context of their use. The conceptual foundation of this approach is the traditional vocational apprenticeship, where a novice learns a trade from a master. The masters share their knowledge with novices, assisting them in developing some skill or product (see Chapter 16 for more information).

Some of the general traditional apprenticeship methods are applicable today. These include observation (of the master), coaching (by the master), practice (by the apprentice), and a fading out of support (by the master), so the apprentice eventually performs the task alone. By remaining actively involved in the learning process ("scaffolding" the acquisition of knowledge and skill), the master ensures that the learner acquires the proper technical knowledge and procedural skills necessary to complete the task. Once the novice/trainee begins to demonstrate proficiency, the master reduces participation (fading), providing only limited hints.

A potential problem with the cognitive apprenticeship approach is that masters of domain-specific cognitive skills may have difficulty articulating their skills to the novice learner, making it hard, if not impossible, for novices to understand. Cognitive research can help in explicating these skills through knowledge engineering techniques. For example, using a probed form of protocol analysis, tacit knowledge of experts can be made explicit (Collins et al., 1989). Once this knowledge is externalized, novices have an opportunity to share in the culture of expertise.

In theory, the main benefit of the cognitive apprenticeship approach is that it forms the basis for deciding which skills should be modeled for or demonstrated to the learner/trainee, how best to provide scaffolding to less-skilled learners, and when to fade such assistance when learners demonstrate they can construct their own meanings and products. Technically, however, the theory does not provide specific guidelines to determine when feedback should be offered, what it should say, or how to determine the optimal level of performance at which fading should begin. Thus, these areas are ripe for empirical research. Three examples (described in greater detail in Collins, Brown, & Newman, 1989) of the cognitive apprenticeship approach are now offered, within the domains of reading, writing, and mathematics.

Reading. Palincsar and Brown (1984) developed a small-group training approach for reading called "reciprocal teaching"—"reciprocal" because learners take on two roles, the producer and the critiquer of knowledge. By reversing roles, students have opportunities to generate and evaluate their own comprehension and that of others. This approach has all of the components of cognitive apprenticeship in that expert skills are modeled to novices, novices are given hints for improving their performance, and assistance is faded once learning has been demonstrated. Some of the relevant expert skills that are demonstrated include formulating thought-provoking questions, summarizing the gist of what has been read, clarifying material, and predicting events (see Palincsar & Brown, 1984, for more detailed information about this training approach, including the role of the instructor).

Writing. Another example of cognitive apprenticeship is the "procedural facilitation approach" to writing (Scardamalia & Bereiter, 1985). In general, novice writers tend to list one idea after another in a "knowledge tell" fashion, while experts organize their writing around emerging goals. Scardamalia and Bereiter decomposed the expert writing processes and developed prompts to facilitate writing plans and procedures for novices. This process includes five general goals: generating a new idea, improving an idea, elaborating an idea, identifying goals, and putting goals into a cohesive whole. Revision is also encouraged. Similar to the reciprocal teaching method, this process involves modeling, coaching, scaffolding, and fading.

Mathematics. The cognitive apprenticeship framework has also been used in mathematical problem solving (Schoenfeld, 1985). In this application, experts use heuristics as well as control strategies and productive belief systems. Schoenfeld describes the selection of heuristics for those problems where a particular heuristic might be relevant, focusing on the use and management of specific heuristics. The expert heuristics are modeled, and students are required to come up with alternative ways to solve the problem. Together, they discuss the usefulness of each heuristic for solving various problems. So students are taught first how to apply the heuristic, then to recognize situations in which it applies. Schoenfeld's method also includes what is called a "postmortem analysis" (also known as an "abstracted replay") where a recapitulation of the student's process is provided, highlighting the critical decisions or actions. Both expert and novice postmortems are discussed in small-groups, enabling students to make explicit comparisons and incremental adjustments to their own performance.

Situated Learning. "Situated learning," or situated cognition, refers to learning in the specific context in which one plans to use the knowledge and/or skill. Problems must be realistic or authentic in the sense that the *applications* of knowledge and skill are readily apparent to learners during the acquisition process. This contrasts with the more typical means of teaching/training where concepts and skills are removed from the context in which they may be used. In fact, a very common criticism of contemporary education is that skills and knowledge taught in schools have become abstracted from their uses in the world (Collins et al., 1989; Resnick, 1987). Resnick examined how learning in school differs from the skills one requires outside school. Schools place a strong emphasis on factual learning, but typically at the expense of more pragmatic problem-solving skills. To supporters of the situated learning approach, this is not just a trend, but a radically new perspective or philosophy that allows for the integration of "psychological theories of physical and cognitive skills, uniting emotions, reasoning, and development, in a neurobiologically grounded way" (Clancey, 1993, p. 98).

The theoretical foundation of this approach is the premise that learners actively construct new knowledge and skills from the world around them (Bartlett, 1932; Collins et al., 1989; Drescher, 1991; Edelman, 1987; Piaget, 1954). Indeed, there is ample evidence that learning is enhanced when instruction is situated in real-world problem-solving scenarios, and where groups of students work out problems together (Brooks, 1991; Brown et al., 1989; Clancey, 1992; Cognition & Technology Group at Vanderbilt, 1992; Collins et al., 1989; Lave & Wenger, 1991; Suchman, 1987). The situated-cognition perspective on the question of where knowledge resides can be seen in the following: "Rather than thinking that knowledge is in the minds of individuals, we could alternatively think of knowledge as the potential for situated activity. In this view, knowledge would be understood as a relation between an individual and a social or physical situation, rather than as a property of an individual" (Greeno, 1989, p. 286).

The Cognition and Technology Group at Vanderbilt University (1992) have been developing a pedagogical approach to situated cognition called "anchored instruction," which attempts to actively engage students in the learning process by situating instruction in interesting and real world problem-solving environments. Rather than teaching students how to solve particular problems, these systems teach generalizable skills, applicable across a variety of problem-solving situations, and designed to be solved by group effort. The major goal of this type of training is to create authentic-feeling environments that allow groups of learners to explore and understand problems and opportunities experienced by experts in a domain, and learn about the tools these experts use. The Vanderbilt group has also developed a series of videodisc adventures for middle-school students, the "Adventures of Jasper Woodbury" series, focusing on math problem formulation and problem solving (Barron et al., 1994). The goal of the project is to facilitate broad transfer to other domains, embodying several design principles: (1) video-based presentation; (2) narrative format; (3) generative learning; (4) embedded data design; (5) problem complexity; (6) pairs of related adventures; and (7) links across the curriculum (for more on this project, see Goldman, Pellegrino, & Bransford, 1994).

One major problem with situated cognition, especially in relation to traditional information processing models, is that it simply has not yet tested the underlying hypotheses that knowledge is better construed as being external to an individual—context-dependent—than as a property of the person. On the other hand, information-processing paradigms have had the benefit of decades of solid research. Vera and Simon (1993), rebutting Clancey's (1993) support paper(s) for situated learning, stated, "Clancey leaves us with philosophy (whether correct or not is another matter), but with precious little science" (p. 118). Because cognitive psychology is an empirical science, studies need to be conducted that address claims made by any new position.

We now highlight a few of the main points from this section (see Table 7-3), then turn our attention to specific variables that influence the way group members interact with one another, and how that can affect learning.

Group Dynamics: Identifying Relevant Variables

We define "group dynamics" as the pattern of group processes such as communication and social control that occurs while a group is interacting in the solution of a problem or task. Various social, psychological, and physical factors have been shown to strongly affect group dynamics, influencing how members of a group interact with one another. For example, communication skills, ability level, gender, and personality all influence group dynamics in specific, and occasionally interactive, ways (Webb, 1991). These factors, and a few others, will be discussed in this section.

The dynamics that transpire within particular groups ultimately impact how well the group as a whole will learn. If data on learner characteristics are available, the structure of a group

Group Training
Summary Statements and Recommendations for Trainers

	Large-Group Training
Workshops	When the curriculum is designed around competent task analysis, and pedagogical decisions are based on empirical research and cognitive/instructional theory, AND there is a match between the goals of the workshop and needs of the trainee, then a workshop can be a very effective way to acquire new skills. We advise caution, however, because often these criteria are not met.
	Small-Group Training
Fostering Interaction	Research indicates that there are a variety of benefits (cognitive, social, motivational) to be garnered from encouraging people to work collaboratively or cooperatively in small group environments. The emphasis here is on maintaining a high and equal level of interaction among group members, thereby giving all participants an opportunity to negotiate meanings, acquire new strategies and skills, and develop higher-order thinking abilities.
Specific Pedagogies	Social constructivism, cognitive apprenticeship, and situated learning approaches all provide empirical evidence that the techniques involved in training with these methods result in deep, meaningful learning and an enjoyable training experience. Some question remains, however, as to whether these results are generally *more* deep, *more* meaningful, and *more* enjoyable than those experienced by trainees working alone. Nevertheless, if the task involved is clearly definable as a group task, we recommend that trainers consider organizing instruction around one or more of these approaches. At the very least, there can be no harm, and it is likely to be the case that training outcome and efficiency will improve.

TABLE 7-3

can be manipulated in order to take advantage of different learner characteristics that would help optimize learning. That is, after identifying the variables that influence group dynamics, research can systematically manipulate these variables to see what the best combinations are to promote learning, for the group and individual. Basic research in cognitive and social psychology continues to seek answers to questions regarding the optimal compositions of learner groups. Is it better to mix genders, or have same-sex groupings? When establishing groups based on aptitude, is it better to match or mismatch abilities? What are the optimal coordinations of personality traits (such as introverted and extroverted)? And what other cognitive/social considerations should be made (e.g., letting individuals self-select their group versus being assigned)?

Communication Skills. One way to investigate group-dynamic factors is to study peer-learning groups in school settings (King, 1989a; Webb, 1985, 1987, 1991). For example, Barnes and Todd (1977) recorded the conversations of students engaged in various problem-solving tasks. Detailed analysis of these conversations resulted in the identification of (1) the nature of understanding that emerges from the group, (2) the kinds of social and cognitive skills required of students for effective interaction, and (3) the effects on interaction of variations in the type of task given to the group. Groups that tended to solicit opinions from all members, encourage precise articulations, ascertain differences among various inputs, and integrate perspectives received the greatest benefits from their interactive experience.

Webb (1993) has suggested that giving and receiving information is more significant in determining the success of group learning than prosocial or basic communication skills. She consistently found that helpful responses are those which elaborate on problem-solving strategies and the rationale behind actions. Unhelpful responses, known as "terminal responses," are those that tell the questioner what to do without saying why or how. "Terminal responses hence fail to empower the questioner to reconstruct the process of finding an answer or solving a similar problem in the future" (Webb, 1993, p. 11). So successful learners in group settings know how to ask the right questions (those that evoke elaborative, rather than terminal, responses). Questions that ask for specific information are more likely to result in specific, helpful responses than general or indirectly phrased, questions (Webb, 1991). Furthermore, it is possible to teach students to ask good questions. King (1989b, 1990) reported positive effects on the level of elaboration in group discussion and on students' comprehension and recall using a reciprocal-questioning strategy.

In addition to the aforementioned communication skills, other powerful techniques that enhance learning include self-explanations (Chi, Bassok, et al., 1989; Chi & VanLehn, 1991; Pirolli & Bielaczyc, 1989) and other-directed explanations (e.g., Palthepu, Greer, & McCalla, 1991). Explaining some concept or skill to oneself and/or to others, combined with the inherent process of meaning negotiation, can collectively be referred to as "knowledge articulation." Knowledge articulation has its strongest impact on learning when it occurs between peers engaged in realistic problem-solving activities; and it significantly contributes more to learning than other important factors such as prior knowledge and age (Chan, Burtis, Scardamalia, & Bereiter, 1992). Bielaczyc, Pirolli, and Brown (1993) found that direct training in explanation and self-regulation strategies such as comprehension monitoring resulted in improvements in learning and problem-solving performance in LISP programming.

In contrast to the view that group-communication skills are effective for social reasons, Chang and Wells (as cited in Cohen, 1994) proposed a group problem-solving model focusing on the management of the problem-solving process through verbal specification of precise goals, planning of procedures, and generation and selection of alternatives. In their view, the effectiveness of the group is a function of its ability to bring the problem-solving process under conscious control. Vedder (1985) agrees with the conceptualization of effective cooperative learning as an explicit process, adding that pupils must control and evaluate their partners' work. He claims that learners in groups must adopt teacher–pupil roles in relation to each other. However, Vedder found that, despite being taught how to regulate one another's solving of geometry problems, pupils spent very little time actually verbalizing their problem-solving strategies. This was corroborated by Webb, Ender, and Lewis (1986), who report that small groups of students learning BASIC programming on a computer did very little long-range planning and performed all of their debugging at the lowest abstract level.

One way to promote effective interaction in small-group settings is to script a dialog for the trainees. A "script" is written very much like a theatrical dialog. Dyads (pairs of learners) read from the procedural text and offer feedback to each other as they perform the actions described in the script. One partner acts as the *planner-performer* and the other as the *listener-observer*, and they then switch roles and continue until the whole procedure is complete. Dansereau and his colleagues have studied the use of this technique in great depth (for the rationale behind the use of scripts in collaborative learning, see Dansereau, 1987, 1988). They provide evidence that, compared with individuals learning procedural knowledge and skills individually, cooperative script use in training results in (1) superior initial performance of the target procedure, (2) better retention of procedural skill and knowledge of the procedure, (3) positive affective reactions to the learning experience and partners, and (4) a superior ability to communicate orally about the procedure (O'Donnell et al., 1988; O'Donnell, et al., 1990). Taken together, these results highlight the paramount importance of effective interactions in small-group training environments.

Ability Level. According to Cohen (1994), one consistent conclusion that may be drawn about ability levels of group members is that low-ability students benefit from being in a heterogeneous group (as opposed to a homogeneously low-achieving group). In contrast, average achievers actually perform better in homogeneous groups. Several studies examining ability groupings on achievement (e.g., Cohen, 1994; Webb, 1982), have found that average students typically do not benefit from mixed-ability environments. Conclusions surrounding the optimal placement of high achievers are slightly more complicated. For example, Swing and Peterson (1982) reported that, within heterogeneous groups, higher-ability students were more likely to offer explanations (consistent with Webb's 1991 findings) and benefit from having verbalized those explanations. Hooper and Hannafin (1988) reported that heterogeneous grouping had no significant negative effect on high-ability students. From these data, a logical conclusion would be that high-ability students should always learn in mixed-ability groups. But other data support a different verdict. Tudge (1991) reported that on a very difficult math task, high-ability learners actually regressed in their thinking from pretest to post-test after working with a lower-ability partner. Thus, "if the task is very challenging and ambiguous and has an ill-structured solution, and if a heterogeneous pair is left alone to agree on an answer, then the confidence of the more developmentally advanced child can be shaken, and he or she may regress to a view of the matter that he or she held at a younger age" (see Cohen, 1994, p. 11).

Gender. As discussed in the section on communication skills, explicit and direct requests for help are more likely to elicit good and helpful explanations than general requests. Research on gender differences has shown that boys are more likely to ask direct questions than girls (e.g., Webb, 1984). Even in cases where males and females are of equal ability, males perform better than females on achievement tests administered subsequent to their group activities. Further, in terms of gender proportions, it seems that groups with an equal number of boys and girls promote more explaining activity than groups with unequal numbers of the two sexes. For example, Webb (1984) examined how gender related to mathematics problem solving for seventh- and eighth-grade students. She found that females in mixed-gender groups (predominantly female) turned to males for assistance rather than to other females because they perceived the males as being more competent at mathematics. Related research has supported this contention by showing a relationship between the perceived status of individuals and the type of interactions that occurred. Webb also reported that in mixed-gender groups (predominantly male), females were often ignored when they asked for assistance. Thus, it appears that mixed-gender groups can occasionally be detrimental to learning by female mathematics students.

The relationship between gender and ability was also examined in a study on learning statistics from a computer-based environment (Lajoie & Lavigne, 1994). Using same-sex groupings of eighth graders, they found that gender plays an important role in group problem solving. Though gender differences did not exist on a pretest of statistical knowledge, differences were found on post-test performance, with a female advantage over males. Thus, providing females with an opportunity to work on group projects with other females (using computers to develop statistical projects) showed a more positive impact than for male-only groups. This study also reported gender differences in learning outcome measures. Journals were given to each group, and students were required to document their acquisition of statistical concepts and skills, as well as their emerging ideas/plans for statistical projects. Female groups tended to document their conceptual knowledge and plans better than the males, whose journal entries were considerably sparser in those areas. However, the male groups' entries were much more complete in regard to answering how they would *apply* statistical concepts in certain situations. Bardos, Naglieri, and Prewett (1992) used a journal-writing approach for documenting evolving knowledge and skills of elementary school students. They similarly reported a female advantage over males in relation to the explication of planning processes. Thus, when the instructional focus is on a particular learning outcome, it may be advantageous to compose heterogeneous groupings (with an equal number of males and females, per group). For instance, if the desired learning outcome is more conceptual, and females show an advantage in this area, then males may benefit from working with females. Alternatively, when the outcome focuses more on the application of certain skills, females may profit from working in groups with males, especially if they receive pretraining in directed-questioning techniques. This technique can help teachers, as well as encourage students to identify concepts and procedures that are poorly understood.

Motivation and Personality. Motivational factors can exert as great an influence on a person's or group's achievement as cognitive factors (Lepper & Chabay, 1985; Slavin, 1983), and motivation levels differ greatly among individuals and groups. Simply placing students into groups and giving them a task is not enough to ensure that they will interact. Individuals need to be internally as well as externally motivated.

Deutsch (1962) originally identified "positive goal interdependence" as the perception on the part of group members that they can achieve their personal goals if, and only if, the other group members also achieve their goals. For this to work, all members should be similarly motivated, and this interdependency has been shown to increase group-learning achievement (e.g., Johnson & Johnson, 1975). A related issue is "positive reward interdependence," which exists when members of a group receive the same reward (external motivation) for completing a cooperative task successfully. Slavin (1983) concluded that achievement is enhanced by cooperative learning when students are rewarded as a group. But he also pointed out that students must be *accountable* for their own learning. Thus, individual accountability is just as important as group rewards. A third interdependency affecting group dynamics has been called "positive resource interdependence," the condition whereby individuals can only achieve their goals when the needed resources (e.g., information) are provided by other members of the group. While Johnson, Johnson, and Stanne (1990) found that neither goal nor resource interdependence promotes effective performance alone, they do enhance group learning when used in conjunction with one another.

In addition to motivational differences among learners, personality differences can significantly influence group dynamics. For example, students in a group can have personality conflicts that counter the positive effects of small-group problem solving. What happens when introverts and extroverts are placed together in a group-learning situation? Lavigne (1994) found that extroverted students are more likely to receive adequate help than the introverted students in the group. The results cited earlier regarding the benefits of asking good questions (Webb, 1991, 1993) and the possibility of training those skills (Swing & Peterson, 1982) suggests that for certain individuals, including introverts, specific pretraining on directive question-asking skills may counter the inequity.

Status. Status refers to any general, agreed-upon rank order for virtually any dimension, where it is typically better to be of a high rather than a low rank. There are systematic and highly predictable inequalities in participation among members of small-groups that are related to status differences between students, with low-status students interacting less frequently and having less influence than high-status students (Rosenholtz, 1985; Tammivaara, 1982). The two types of status differences that seem to have the greatest effect on interaction are those related to ability and popularity. In the case of ability (academic status), it is *perceived* rather than *actual* ability that determines differences in rates of participation. For instance, Dembo and McAuliffe (1987) reported that higher-status students (defined as those publicly assigned above-average scores on a fake test) dominated group interaction, were more influential, and were more likely to be perceived as leaders than low-status students. Popularity (peer status) is often highly correlated with academic status. Therefore, differences in perceived attractiveness or popularity can also be the basis for status differentiation (Webster & Driskell, 1983).

There are several ways to counter the potentially negative influences of status on group dynamics. One intervention is the "multiple ability treatment." Teachers using this technique convince students that there are many different abilities relevant to the group task, that each member of the group will have some of these abilities, and that no member of the group will be good at all of the tasks. In both laboratory (Tammivaara, 1982) and classroom (Rosenholtz, 1985) experiments, this technique has substantially weakened, but not eliminated, status effects. One must be careful in choosing applications of this technique, however, because even with true group tasks, it is feasible that a single person could be good at all of the requisite tasks. Assigning competence to low-status students is another treatment option. In this case, teachers make a special effort to publicly applaud the efforts of low-ability students whenever they demonstrate some higher-level intellectual competence. By pointing out what the low-ability students did well and how it contributed to the group effort, the instructor makes it more likely that low-ability students will be included as equal members of the group during future tasks.

Task Characteristics. The just-described research relates to learner characteristics that affect group dynamics and ultimately learning; variables related to the nature of the task, itself, can impact group dynamics as well. For example, Webb (1983, 1991) has concluded that there is no main effect of simple frequency-of-interaction on an individual student's achievement. Most of these studies took place in math classes where students were put in groups and told to help each other solve problems, asking the teacher for help only when no one in the group could assist. But the opposite has been reported by Cohen and her colleagues (Cohen, Lotan, & Leechor, 1989), who "consistently find that simple measures of frequency of task-related interaction are related to gains in computation and mathematical concepts and applications as well as in content-referenced tests" (Cohen, 1994, p. 7).

These disparate results may be explained in terms of the nature of the respective learning tasks, and how they may have affected the working relationships among group members.

Most of the tasks in the math and computer group studies examined by Webb were not inherently group tasks; they could have been completed by individuals. A group task may be defined as "a task that requires resources (information, knowledge, heuristic problem-solving strategies, materials, and skills) that no single individual possesses so that no single individual is likely to solve the problem or accomplish the task objectives without at least some input from others [Cohen & Arechevala-Vargas, 1987]" (Cohen, 1994, p. 8). Cohen's studies, on the other hand, were conducted on complex instruction in multilingual classrooms and *did* involve genuine group tasks. In particular, instruction was embedded within ill-structured, open-ended discovery environments; the problems were conceptual tasks that emphasized higher-order thinking skills. In addition, students in Cohen's studies underwent a week of skill-building activities focusing on mutual assistance. Steps were taken to prevent large disparities in helping behavior. The studies reviewed by Webb included neither a system of classroom management nor special training for the small-group environment. The nature of the work assigned to the groups varied. On the one hand, solving math problems is a well-structured activity with definite correct answers, while on the other hand, open-ended discovery problems used in complex instruction could have a variety of correct answers. Cohen's general conclusion is that "given an ill-structured problem and a group task, productivity will depend on interaction" (Cohen, 1994, p. 8), and the benefits to group learning will increase in proportion to the amount of pre-training that students receive on how to interact with one another.

In conclusion, groups sometimes do, and sometimes do not, work well together. The success of group learning has been shown to depend on a number of variables, working independently or in concert with one another. Although more controlled research is needed to begin filling empirical holes and derive concrete principles, it is possible to present preliminary guidelines for making decisions about optimal groupings for different learning/training conditions, as we do next (see Table 7-4).

The foregoing reviews were not specifically bound to either human- or computer-based training; the following subsection specifically addresses how small-groups may learn from computers.

Group Learning on Computers

There are basically three ways to implement collaborative learning environments using computers: (1) a small-group of learners interact with each other on a single computer system; (2) the computer system itself serves as the "partner" in the collaboration; or (3) students collaborate with each other, but are located at sites distal to one another and to the teacher/trainer. The first implementation—a small-group using one computer—represents an extension of the research (just cited) on collaborative learning in classrooms. The main issues that need to be addressed are that the computer system must be able to: (1) introduce knowledge into a joint problem-solving space; (2) monitor ongoing activities for evidence of divergences in meaning; and (3) repair divergences that impede the progress of the collaboration (see Teasley & Roschelle, 1993). Where this list differs from the components of underlying traditional student modeling (see ITS subsection "Individualized Training") is that modeling a group is built on a joint, rather than single, problem-solving space. Simply put, the ITS must take into account the fact that there are multiple learners working together concurrently by either maintaining a separate student model for each learner or "averaging" across their responses to create a single model for the group.

A second way of implementing collaboration involves assigning the computer to be the learner's partner. This represents an intriguing twist on the notion of collaborative learning. To illustrate, Cumming and Self (1989) proposed a collaborative Intelligent Educational System (IES) with the goal of engaging the learner in a partnership. Here, the computer serves as a collaborator, not as an authoritarian instructor. In both cases, a student model must still be derived of an individual or a group.

"Distance learning" represents a third way that computers can be used in collaborative learning (Stephenson, 1992). In this case, students are physically separated from each other and from any teacher or trainer. Each student has his or her own computer, and interactions are achieved electronically. The effects of this approach, in relation to the other kinds of collaborative environments, are not known. We know of no studies explicitly testing whether electronic interaction is as beneficial, in terms of outcome, as the positive influences of face-to-face interaction. Furthermore, because learners are located distally, they cannot point out interesting features on the shared computer screen, although visual, and possibly voice, interactions could still ensue over the network. This type of arrangement also decreases the strength of one of the main arguments in support of collaborative environments, namely, that it attenuates resource limitations by distributing few computers among many learners. On the positive side, distance learning can allow learners to stay at home or some other convenient location (saving time and transportation costs), and connect to a network of information and training software (see also Chapter 15).

Designing and developing computer-based group-learning environments requires an integration of the social, cognitive, and conative factors that affect group-learning processes and outcomes. Moreover, one must determine ways to manipulate (enhance or attenuate) these factors with a computer. The specific implementation depends on the nature of the interaction (i.e., several students around one computer, a student in collaboration with a computer partner, or students using different networked computers). This is not a trivial task. Consider the difficulties encountered in trying to understand how and why groups differ in their learning outcomes, and how the tutor influences that process. Then imagine being a software engineer, trying to draw on that relatively limited (but growing) body of knowledge in an effort to make a computer "seem like" an expert instructor, or another student with whom the human will collaborate. Finally, the issue of interface design must be addressed. Taken together, this whole enterprise of designing computerized group-learning environments is extraordinarily complex.

To illustrate some of these complexities, we cite a recent effort by Blandford (1994), who created an IES called WOMBAT (Weighted Objectives Method By Arguing with the Tutor). WOMBAT is designed to teach in the domain of design decision making and to act as a collaborator in the problem-

Group Dynamics
Summary Statements and Recommendations for Trainers

Communication Skills	The findings are very clear with respect to this variable. Trainees *must* communicate well with each other in order to take advantage of all that the small-group learning environment has to offer. If they are not doing so, they should be *trained* to communicate productively. Communication skill training should focus especially on (1) the development of academic help skills (e.g. asking questions that require specific information and elaborative responses, responding to questions by elaborating on strategies and rationales), (2) encouraging participation in knowledge articulation, and (3) learning to explicate goals, plans, and alternatives during the problem-solving process. Dialogue scripting seems to promote effective interaction, and should be considered a potential means to that end.
Ability/Aptitude	Research shows that low-ability trainees will learn better in heterogeneous groups, while medium-ability learners should be placed in homogeneous groups. High-ability subjects should learn within mixed-ability groups when the task is relatively simple, but in homogeneous groups (all high-ability) when the knowledge and skills to be acquired are very complex.
Gender	When there are equal numbers of males and females, one should mix the groups by gender. Females should receive supplemental training in asking direct, explicit questions prior to group learning activities.
Motivation	The training experience will be more productive when learners are both internally and externally motivated. To encourage this, trainers should do what they can to ensure that group members share a perception of goal and resource interdependence, that all members of the group receive the same external reward for training performance, and that they all feel personally accountable for their own learning within the context of the group.
Personality	Extroverted and introverted personality types should be mixed within small-groups, but one should provide some kind of pretraining in communication skills to the introverts.
Perceived Status	The perception of inability and/or unpopularity has serious negative effects on participation in small environments, and therefore on training outcomes as well. Potential status effects may be countered through the use of intervention techniques like multiple ability treatments and assigning competence to low-group-ability learners/trainees.
Task Characteristics	The greatest benefits of small-group training will be realized when the tasks involved are *true group tasks* that require resources that no one trainee possesses and that will require at least some input from others. Of the group tasks, ill-structured tasks require productive communication among group members in order for everyone to achieve mastery of the domain.
Summary	*Trainers should be cognizant of person and task variables and the ways they influence group dynamics. While making decisions about group composition, it is important to consider that these variables do not exist independent of each other. That is, any given trainee will be not only male or female, high-ability or low-ability; rather, each individual will be a complex melange of all of these characteristics. Where possible, combinations of decision rules can be used to maximize learning for all trainees. Considerably more empirical research is needed in the area of group dynamics.*

TABLE 7-4

solving process. It was designed to be used individually, and the *computer* acts as the collaborating learner. It includes a dialog agent that (1) prompts users to think about and justify their decisions, (2) discusses not only aspects of the problem, but also how it is to be solved, and (3) accomplishes all of this in a non-prescriptive manner, such that the computer does not behave as if it knows all the answers. In a recent formative evaluation study, ten subject experts, all of whom tested out the program separately, concluded that, although this dialog agent was an important enhancement of the system, the overall interface of the tutor made it fairly difficult to use. Thus, not only *what* the program is designed to do, but *how* it is implemented on the screen must always be taken into account. A well-designed program that is confusing to the user loses much of its potential educational value.

Despite the difficulty of the endeavor, CBT and ITS can be extended for group work. Stephenson (1992) conducted a review of 30 studies that focused on comparisons of achievement between individual and small-group CBT. He reported that in no case did individual CBT produce statistically higher achievement than small-group CBT, and that there was no evidence that pairing students for CBT work lowers achievement. In fact, in 11 of the 30 studies, small-group CBT students performed significantly better than individual CBT students. Of the studies with nonsignificant results, Stephenson points out that many of them involved fairly short experimental sessions (one session of less than 60 minutes or several sessions totaling less than 120 minutes). Moreover, dependent variables were assessed only via brief paper-and-pencil tests, or computer-based multiple-choice exams. One lesson here is that experimental sessions should be fairly long and intellectually challenging, and the outcome measure should be difficult enough to allow for some variability. Another lesson is that the longer the training time, the more likely it is that group CBT work will result in higher outcome.

Stephenson's review establishes a strong basis for the general conclusion that small-group CBT work is consistently more effective than individualized CBT training. Why might this be the case? There are many potential explanations, but we feel this result is primarily a reflection of the inherent power of small-group interaction. Two or three learners working together at a single computer are able to scaffold each other's learning, act as surrogate tutors, attend to the subtle response cues that the computer cannot understand or even perceive, and then generate immediate, appropriate, helpful feedback.

Cohen's recent conclusion that "either through some kind of motivational device or through deliberate instruction in these social skills, something must be done to provoke the desired behaviors within cooperative groups" (1994, p. 7) is as true in the case of computer-based group training approaches as it is for a group of humans collaborating on a problem. As guidelines for the development of computerized group training environments begin to develop, the emphasis should be on maximizing the potential for productive *interaction* (among humans, and between humans and the computer), just as it is in all-human group approaches.

Katz (1995), in apparent agreement, calls for a methodology for developing computer-supported collaborative learning (CSCL) environments. She posits that CSCLs should: (1) offer direct guidance and structuring of peer interactions, in an attempt to prevent problems like the "free rider" effect (some learners not participating in the task) and the diffusion of responsibility; (2) give students something challenging to talk about (e.g., employ conversational tools such as menus that prompt for components of a dynamically constructed explanation and provide questioning stems) (Katz & Lesgold, 1994); and (3) enable collaborating peers to resolve conflicts when they arise, because it is conflict resolution, rather than the existence of conflicting viewpoints, that promotes learning.

A lot remains unknown in the area of group approaches to instruction. So many variables affect group dynamics in the "all-human" learning environments alone that it will probably be a number of years before a fairly complete set of specific guidelines can be compiled. Until that time, attempts to create effective computer-based group learning environments will continue to be plagued by some of the same problems afflicting group learning in general (as well as those unique to computer-delivered instruction). The problem is that we do not really know what to tell the computer to do, or how to do it, or even when it should be done. Modeling even one student's ability and skill level has proven to be very challenging. Attempting to do the same thing with a small group of students (even just two) seems a bit premature. In summary, group training environments, whether delivered by a human or computer instructor, should be designed to *guide* students to think for themselves and prompt them to communicate with each other to work out misunderstandings and impasses along the problem-solving pathway. Without the right kind and degree of support, students often fail to interact fruitfully. A well-designed group-training environment should be capable of providing students with domain-specific knowledge as well as domain-independent communication and learning skills (see Table 7-5).

DECISION TIME: INDIVIDUAL OR GROUP APPROACH?

Before any specific decision can be rendered on whether to employ individualized or group training methods, more controlled research studies need to be conducted that explicitly test the relative efficacy of these training approaches, within and across domains. For a variety of reasons (e.g., greater range of shared knowledge, resource limitations), the notion of group learning environments is appealing. However, many unanswered research questions need to be addressed (see Katz & Lesgold, 1993). These include: What parts of the curriculum should be trained in groups, and what parts learned individually? What teaching methods should be used to achieve the instructional goals, and how should they be sequenced to optimize learning? What should be the role of the human or computer tutor? We start by identifying some general training issues, followed by a brief discussion on these three questions.

GENERAL TRAINING ISSUES

The design of any training program (individualized or grouped instruction) should start with a broad cognitive task analysis of the targeted task or curriculum. Tasks may depend on greater or lesser contributions from declarative knowledge, procedural knowledge and skill, or other performance skill determinants such as perceptual motor skill. These categories of cognitive operations may be viewed as lying along a continuum that runs from more knowledge-based to more performance-based (for more on this topic, see Kyllonen & Shute, 1989).

Though most complex tasks are supported to some degree by all of these categories of cognitive operations, many tasks are heavily weighted toward one end of the continuum. For example, some tasks are very knowledge-based (e.g., electronic troubleshooting or medical diagnosis) and others tend to be more performance-based (e.g., cutting a diamond or flying a fighter jet). Knowledge-rich tasks tend to require associative learning skills and elaborative processing, and are typically well suited to small group instruction. In contrast, performance-

Computer-Based Group Training
Summary Statements and Recommendations for Trainers

Small-Group CBT	Small-group CBT occurs when two or more trainees sit down at a computer monitor (or at separate, networked monitors) and learn from a non-intelligent software program. In other words, there is no modeling going on. Results indicate that working in small groups with computerized training software leads to equal and often greater outcome than individual CBT work. The implication, then, is that there is much to be gained from having people learn together at the computer and nothing to lose.
Small-Group ITS	The addition of any sort of intelligent component to a computer-based, small-group training environment takes us well down the path into uncharted territory. Only the very first steps are being taken in this direction, even as this chapter reaches completion. The complexities involved in this stream of research are profound and intimidating, but given the positive results found with standard CBT group work, we anticipate promising results from those creative souls at the forefront of this effort.
Summary	*Clear communication and productive interactions are just as important here, and perhaps more so. Whether your small-group training will include CBT or ITS work, trainees should be prompted to ask direct, specific questions, and to provide elaborative responses. Again, if they are not doing this, it is necessary to train them to be better communicators.*

TABLE 7-5

based tasks require an assimilation of the required knowledge and procedures to the point where conscious effort is no longer required or may even be detrimental for superior task performance. Such assimilation, or "automatization," (see Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) requires extensive practice, and these kinds of tasks may be better suited to training that allows sufficient individualized practice of component skills.

TASK (OUTCOME) BY TRAINING APPROACH (INDIVIDUAL OR GROUP INSTRUCTION)

The results from a cognitive task analysis represent the first step in the decision to adopt either individualized or group training approaches. For instance, within a given domain (e.g., statistics), some of the primary tasks or desired outcomes may be declarative or conceptual knowledge (knowing that the symbol Σ means "the sum of," or understanding the notion of variability within a set of data). Alternatively, within the same domain, the desired outcome may be procedural (demonstrating skill in computing the variance of a set of data). The "flavor" of the cognitive task analysis is dependent on what the trainer wants the trainee(s) to walk away with at the end of the training session. In other words, depending on the specific desired outcome(s), the training program should reflect the underlying cognitive operations that support performance in the targeted task or task component.

Results from the literature cited in previous sections of this chapter and elsewhere seem to indicate that task components, or curriculum elements, that fall more on the knowledge end of the continuum are amenable to group training. These elements, or knowledge components, can be arrayed in terms of their relative complexity, from simple propositions to schemas to more complex mental models (see Shute, 1994 for more a more thorough discussion of these outcome types). Similarly, task components that reside more on the performance end are probably best instructed individually if there are with more hands-on practice opportunities available. However, this remains an empirical question, ripe for further research (for instance, one study might make an explicit comparison of a complex task instructed in a group setting compared to an individual setting). Finally, it should be noted that various parts of the curriculum can be instructed differentially; certain tasks can be trained within small groups, while others (within the same training session) can be taught individually.

TASK (OUTCOME) BY TRAINING CONDITION

Once the curriculum or task has been decomposed and a preliminary decision rendered about training approach (individual or group), the teaching methods need to be selected to accomplish the specific training goals. There is a wide range of potential teaching methods to choose from in designing a training program. One way to view these methods or training environments is along a continuum, from maximal trainer control (as in rote learning conditions) to very minimal control (as in discovery worlds). Figure 7-6 illustrates such a continuum.

Suppose the instructional goal was for trainees to acquire conceptual knowledge of the operation of a nuclear power plant, to understand the functional relationship among the nuclear reactor, steam generators, and steam turbine system to produce electricity. What is the optimal training environment to produce this learning outcome? One possibility is to employ a guided-discovery environment where small groups of learners work together to understand the different parts and functions of the power plant and then discuss the ensuing ramifications (see Bennett, 1992). In contrast, suppose the instructional goal was the acquisition of a specific procedural skill, such as controlling the flow of feedwater in a power plant (manipulating the rate at which feedwater returns to the steam generator). According to

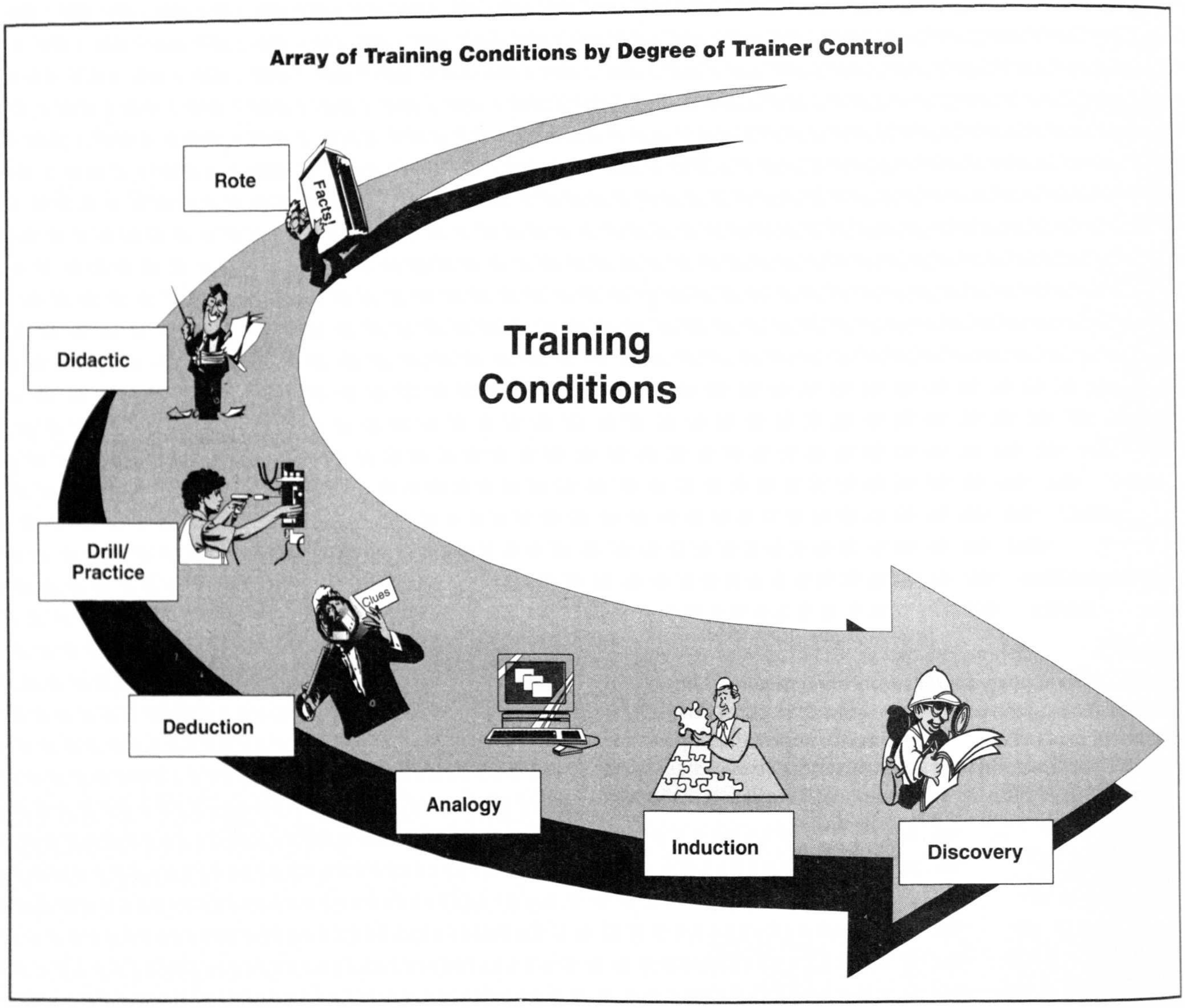

FIGURE 7-6

Bennett, experts can quickly recognize problems in feedwater levels, select an appropriate strategy, then execute that strategy in an automatic fashion. To achieve this training goal, one could use a drill-and-practice environment to ensure proceduralization of component skills. This would involve presenting a sufficient number and variety of problems (e.g., varying feedwater levels and related components) to promote fluid and generalizable performance. This is not to suggest, however, that drill-and-practice on component procedural skills would be the only training method used, or that subjects would be left unattended in automatizing these procedures. One must also ensure that the procedures acquired are the correct ones, as specified by experts in the domain.

TEACHER/TRAINER ACTIVITIES

Cohen (1994) succinctly identified one of the thorniest issues regarding the teacher's role within various instructional environments, relevant to both human- and computer-delivered instruction. She states, "Herein lies the dilemma: If teachers do nothing to structure the level of interaction, they may well find that students stick to a most concrete mode of interaction. If they do too much to structure the interaction, they may prevent the students from thinking for themselves and thus gaining the benefits of the interaction" (p. 22). Thus, trainers walk a fine line between sufficient and insufficient intervention.

Cohen, Lotan, and Leechor (1989) found a negative relationship between talking and working together among students and the rate at which the teacher used forms of direct instruction when students were working in small groups. In order for collaborative or cooperative learning to take place, teachers must be able to delegate authority so that more children can talk and work for longer periods of time at multiple learning centers in the same classroom, or even in distal locations. And there are other roles that a teacher can adopt in small-groups, such as lecturer, coach, facilitator, or collaborator, that may foster interactions and lead to conceptual gains, particularly for problems with ill-structured solutions.

"Meta-coaching" has been suggested by Katz and Lesgold (1993) as an appropriate role for the human or computer tutor. This means that the coach should guide students as they learn, either in individualized or small-group settings. Katz and Lesgold have recommended that coaching should be highly interactive and in the form of questions that guide students in actively overcoming impasses instead of directing them what to do. When employed in group-training environments, Merrill et al. (1992) refer to this process as "collaborative error repair." Fox and Karen (1988) also examined effective behaviors of human tutors and found they often engage in a process they refer to as "collaborative cognition," the explication of one's thoughts during problem solution.

The timing of this coaching activity has also been investigated in relation to the learning/training process. When is the best time for the trainer to intervene? Several researchers have concluded that the best time to provide assistance is exactly when an impasse occurs (Anderson, Boyle, & Reiser, 1985; Corbett & Anderson, 1989; Kulik & Kulik, 1988; VanLehn, 1988), and students can immediately try out the advice or information received (Vedder, 1985). Another perspective on this timing issue is for the coach to intervene only in cases where students are clearly floundering. This position posits that it is better to develop an environment that contains assorted tools where learners have the freedom to explore and learn mostly on their own, with minimal intervention (e.g., Collins & Brown, 1988; Shute, Glaser, & Raghavan, 1989; White & Horowitz, 1987). But again, this disparity between perspectives is confounded because the real issue is not which is the better training environment; but rather, which is the better environment for what type(s) of person (Cronbach & Snow, 1977).

CONCLUSIONS AND GUIDELINES

Across numerous studies we have seen that learning is a direct function of effective interactions—between trainer (human or computer) and trainee, as well as among trainees. This remains true regardless of differing learner and task characteristics, instructional approaches, and training environments. Whether instruction is delivered by a human or a computer, or in an individualized or group setting, students' learning is strongly influenced by their interactions (e.g., communication processes, assistance through impasses). Although the success of these interactions is influenced by trainee and task characteristics, the *quality* of the interactions is ultimately what determines the degree of knowledge and skill acquisition.

How can one enhance the quality of the interaction? We have reviewed various studies examining what expert teachers and effective computer systems do. Experienced human teachers/trainers monitor and alter interactions instinctively, taking into account many variables, including some that computers currently do not have access to (e.g., facial expressions, paraverbal cues, prior experience teaching the subject matter). To achieve a comparable degree of effectiveness, computerized training systems must accurately diagnose learners' knowledge and skill status, and use this information to make curriculum changes and create appropriate feedback. In addition to tutor-specific response histories (which often form the basis for inferences used in computer-based diagnoses), additional trainee information could be assessed by computers (e.g., aptitudes, personality, learning style, gender, interests, social skills; see, for example, Shute, 1995; Snow, 1992; Tobias, 1994), provided there is an empirically based rationale for using each specific piece of information about a learner in making curriculum or pedagogy decisions. Finally, the computer's interface must also be clear and easy to use in order to facilitate the interaction process.

Group-training approaches place an even higher emphasis on interaction, but their focus is more on interactions among students than between students and trainer. Variables relating to group dynamics (e.g., positive goal interdependence, gender and ability composition) must be considered in addition to the diagnostic and pedagogical concerns mentioned above. Because not all groups work well together, some degree of supervision and guidance is needed during group learning. Just as students can be guided to discover their own errors and solutions during individualized instruction, tutors (whether human or computer) should prompt small groups of students to discuss certain topics, compare and contrast differing viewpoints, ask specific questions, offer appropriate responses, and generally maximize the benefits inherent in their continuing interaction. It is also important to minimize the impact of negative influences on group learning, such as status effects and "social loafing."

Because there are too many gaps in the literature on the interactive effects among the multitude of variables comprising any training environment, simple and straightforward recommendations cannot be made about when to use group instead of individual training, or whether to use humans or computers as the instructional medium. Figure 7-7 shows the factors that should initially be considered when making training decisions.

As shown in the figure, these three variables (characteristics of the task, learner, and resources) need to be considered concurrently, and will constrain subsequent decisions about which specific pedagogical approaches should be implemented. These three factors can be viewed as "givens." For example, if you have no computers on which to train, then you are constrained to deliver instruction by humans or paper-and-pencil methods. But even under this option, you are still confronted with instructional decisions, such as how to structure the learning environment (e.g., employ cognitive apprenticeship, provide one-to-one tutoring). If you do have computers and software available for teaching the task or specific components of the task, your options are even greater.

As discussed earlier, some parts of the training (procedural skills) can be instructed by the computer, while other parts are taught by a human tutor. If you decide on computer-based instruction, you have further options, in terms of whether you should employ CBT, ITS, a simulator, or a discovery world. Before making the decision regarding individualized or group instruction, you need to ask, is this task component amenable to group training? Only tasks that are specifically designed for group learning should be completed by groups; otherwise, the exercise will seem artificial to the students. That is, you want

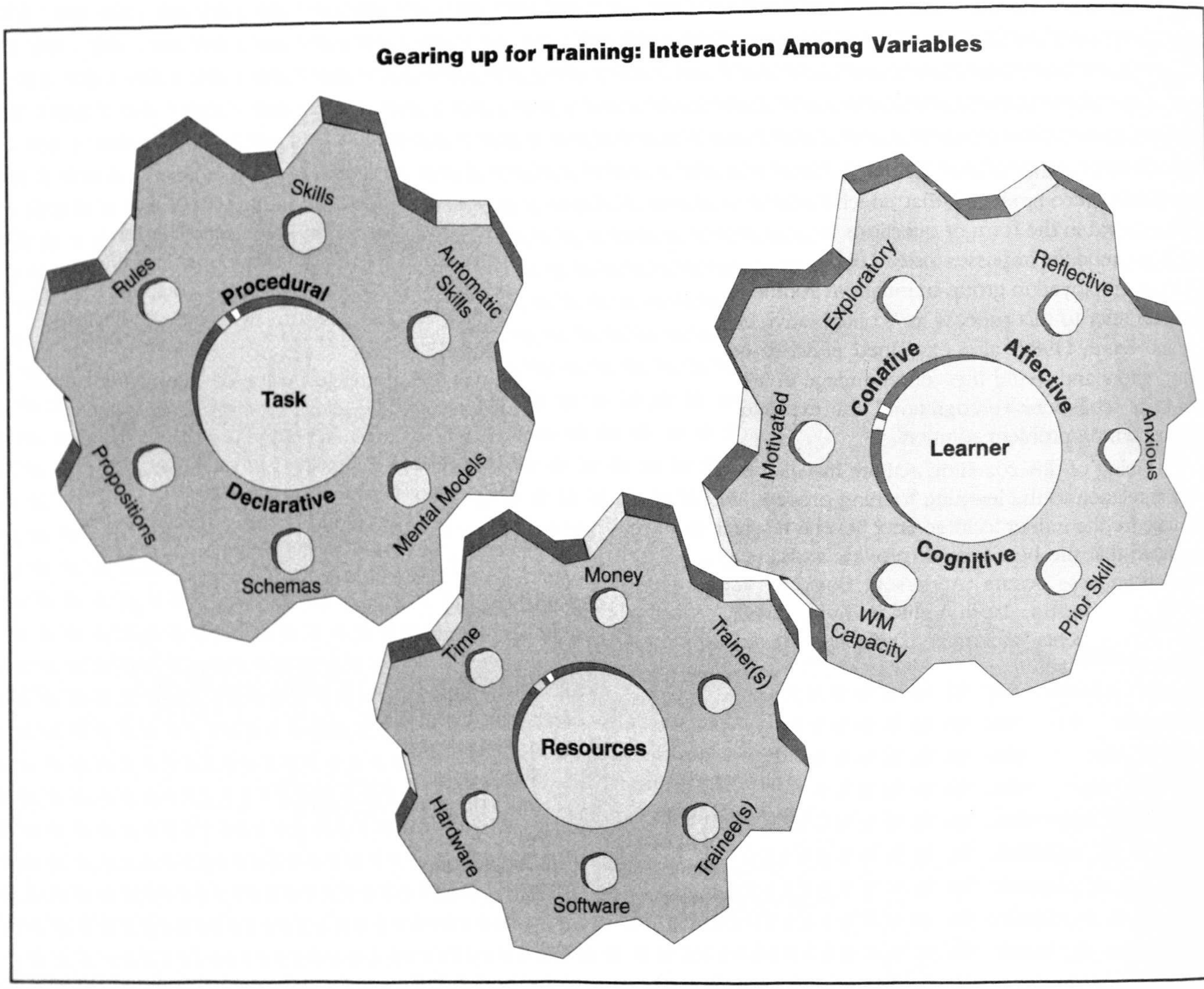

FIGURE 7-7

the *task* to determine which training approach to take, rather than deciding on an approach and then jury-rigging the task to fit. Following are two illustrations of how decisions can be rendered about training, given certain constraints on the task(s), learners, and available resources.

GUIDELINES BY ANALOGY

Scenario 1

Suppose you were preparing to instruct 30 trainees on a particular task, such as air traffic control. You begin by assessing the first of the three main variables: (1) *What are the goals of the task?* At the end of training, you want your students to possess knowledge of such information as air traffic control rules, weather and aircraft radar, styles and fuel capacities of different aircraft, special kinds of emergency situations, and various runway characteristics. Also, the trainees should evidence automaticity in performing the following component skills: guiding planes in for a landing under adverse weather conditions, plotting holding pattern routes for delayed aircraft, interpreting information from radar screens, and making decisions under stressful conditions. Next, you need to assess the characteristics of your trainee population: (2) *What are the characteristics of the trainees?* You note that the group appears to be quite diverse in terms of background knowledge, skills, and other aptitude measures. For instance, half of the trainees have had some related background experience (e.g., some have worked as pilots, flight engineers, and radar operators) while the other half are complete novices. Should all trainees receive the same curriculum, or can it be altered to fit their respective backgrounds? Finally, you need to assess what is available to you in terms of resources: (3) *What resources are available to deliver the training?* Because you are subsidized by a large corporation, your resources include a sufficient number of computers to provide individualized instruction (if appropriate), various software packages to supplement training (e.g., simulations and other CBT), and a period of one month to train this group.

The top-level decision that needs to be made involves specifying the instructional approach(es) to train this diverse group of students on the various knowledge and skill outcome types. Given the constraints illustrated above, this decision specifically addresses whether training will occur in an individualized or group setting. You note that certain portions of the training program are better suited to individualized instruction (e.g., the parts that are procedural in nature and that would benefit from extended practice). For instance, students could be trained to interpret radar data quickly and accurately by viewing and responding to many and varied radar patterns, and then individually performing the identification procedure repeatedly. Other parts of the curriculum are more suitable for group approaches. For example, small groups of trainees could converge to discuss differences and similarities among aircraft, debate alternative actions to be taken under various adverse weather conditions, and so on. In addition, trainees with more background experience could serve as facilitators in these small-group discussions, benefiting themselves and the other members of the group by articulating their knowledge.

The second level of decision addresses the specific training approach to be used, either in human or computer-delivered instruction. For the small-group learning tasks, you decide to employ the cognitive apprenticeship model as you have a range of talent in your pool of trainees to serve as facilitators and/or coaches. For task components that you have determined should be instructed by CBT, you decide to use the drill-and-practice software for the presentation of alternative radar patterns, and the training-by-analogy software for teaching decision-making under stressful conditions. "Training by analogy" software is designed to present the learner with a wide variety of analogous situations that all involve some common theme (e.g., a particular complex cognitive task), with the goal that enough exposure across a variety of specific scenarios will facilitate transfer to other domains. While this scenario could conceivably have employed alternative decisions about training, we have tried to derive decisions that are based on the research cited within this chapter, making our "best guess" as to optimal training techniques. We have not attempted a response to every issue that would arise in preparing a training program like the one in this example. Rather, it is our intent to provide some preliminary samples of the types of thought processes trainers should go through in designing creative new training programs of their own. A second scenario is now presented that reaches different conclusions based on an alternative set of constraints.

Scenario 2

Now suppose that you are getting ready to instruct 100 students who have enrolled in your introductory microeconomics course at the local university. Your training/instructional goals include having the students exit the course with a conceptual understanding of the laws of supply and demand, and how they operate within and across a variety of environments. In particular, you want learners to understand the functional relationships among relevant variables such as price, quantity demanded, demand, supply, equilibrium, interest rates, income, and so forth as they interactively impact different markets (e.g., coffee, tea, compact cars, gasoline). These constitute your "task" constraints. Furthermore, you are informed that these students are all fairly homogeneous in background in that none have ever had any prior economics courses or training. Also, half of the students are male and the other half female. Finally, you have at your disposal a computer laboratory with 50 computers and some software that you obtained from a colleague; it is a microworld called "Smithtown" that provides a guided-discovery learning environment for inducing principles of microeconomics (Shute & Glaser, 1990). Finally, the duration of the course is six weeks, with three two-hour classes per week.

As in Scenario 1, the top-level decision addresses what parts of the curriculum should be administered individually, and what parts should be administered in a group setting. After reviewing your constraints, you decide that, given (1) the nature of the task (which consists of declarative knowledge as well as procedural skills), (2) the similar background of the learners, and (3) the exploratory software and 50 computers, you will lecture to the group the first hour of each day, then assign learners to mixed-gender dyads for the second hour of class. The lecture part will be instructed by you to all 100 students, imparting your vast knowledge of microeconomic variables and principles. The computer laboratory will allow the learner pairs to apply their new knowledge and skills to hypothetical situations that they create themselves. Also, because microeconomics can be viewed as an ill-structured domain (alternative solution paths are possible), you are confident in your decision to employ a small-group training approach in conjunction with the lecture as it represents an optimal blend of instructional techniques.

As can be seen in the foregoing scenarios, decisions must be made at various levels to optimize training, *given a set of constraints under which to operate.* The first-level decision concerns individual or group approaches to training. The second-level decision involves human or computer delivered training, both with advantages and disadvantages. For example, while computers can record and reproduce every action a student makes during problem solving, they currently have limited communication potential. Humans provide much more subtle, complex, and flexible feedback, but they also might lose their patience or forget to mention an important point.

Lepper and Chabay (1985) noted that computer-based training environments possess the potential to be particularly valuable research tools, and that they should be used to investigate many of the assumptions currently underlying various educational theories and practices. Though this research is ongoing in laboratories and classrooms all over the world, to date there simply have not been enough controlled evaluations of computer tutors (especially in comparison with human tutoring) across varying domains to allow for any hard and fast guidelines at this level. Realistically, the determining factor is the financial resources of the trainer(s) and/or availability of good human tutors, rather than potential for instructional benefit. Good human tutors are usually considered experts, and their services are not cheap. In addition, the price of the decision to go with a human tutor increases as time goes on, since you have to continue to pay them for their efforts. Computer tutors, on the other hand, initially involve a significant development and implementation cost (purchasing the hardware, programming the software), but once the product is in place, the cost of running the program is minimal. When it is only necessary to train a few individuals over a relatively short period of time, a human tutor probably makes more sense, with the current state of technology and resource availability. But organizations that train large numbers of people, especially over a long period of time, will likely find the computer-based approach more cost-effective in the long run.

More specific decisions are required in addition to the higher-level decisions (i.e., individual or group and human or computer training). For instance, when deciding on a group training approach, the subsequent decision addresses whether students should work collaboratively or cooperatively. Once again, the specific nature of the tasks themselves, as well as desired outcome, should influence this decision. Collaborative work will generally result in a higher frequency of interaction among group members, and thus a deeper level of cognitive processing and a better conceptual understanding of the problem space. Cooperative learning is more likely to result in individual accountability and increased efficiency, but offers fewer opportunities for interaction among group members. Thus, tasks that have a strong conceptual flavor and that are fairly challenging are probably more effectively trained in a collaborative setting than a cooperative one. We now conclude this chapter with some ideas about the impact of individual and group approaches for future training research and applications.

SPECULATIONS ABOUT THE FUTURE

Technology is evolving to the point where computer systems can contain learning environments that support a high level of social interaction. As discussed in this chapter, this is important in facilitating effective learning, both within the classroom and from computers. The atmospheres in classrooms containing a connected computerized environment are similar to what Feurzeig (1988) found in a collaborative mathematics course that was "more like a beehive than a math class" (p. 117). In time, these collaborative classrooms can eventually support networked computer stations. This means that students, trainees, and experts can interact between schools and remote sites, and trainees and instructors can share the same experiences. Learners can work collaboratively on the same project or different students can work on the same project at the same time, without awareness of each other's presence (but with some invisible instructor standing over them). The number of combinations is great, and their learning/training potential is unknown.

Over the past 25 years, two parallel research streams have changed the face of training: (1) new approaches to group training (such as cognitive apprenticeship and situated learning) have been defined and researched and (2) computers and associated instructional software have become increasingly prevalent in the classroom and workplace. Thus, the current state of training is considerably more sophisticated and offers significantly greater options to trainers than in the past. But has there been a corresponding increase in effectiveness and efficiency? The answer is inconclusive. In order to maximize learning outcome and efficiency (to meet Bloom's 2-sigma challenge) considerably more research is needed, particularly in the area of interactions among variables known to influence learning and training. Regarding individualized instruction, more controlled studies are called for that systematically test for individual differences, as well as aptitude-treatment interactions (or families of aptitudes and treatment conditions), within and across various tasks. These related avenues should prove fruitful, especially using the controlled environments inherent in computers. Furthermore, the findings can directly influence the design of instructional approaches to increase adaptability and effectiveness. In group training research (with human or computer-delivered instruction), similarly controlled studies are required that examine main effects and possible interactions among variables that are known to impact group dynamics (e.g., gender, ability, personality, status). This will provide important information about optimal groupings of trainees within and across domains. The future direction of training is resolutely dependent on the findings from basic and applied research studies. Our hope is that this chapter may excite and incite such research.

NOTE

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