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LEARNING THEORY AND THE STUDY OF INSTRUCTION

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This article examines the articulation of learning theory that is emerging from studies that take principled approaches to the design of instruction of complex forms of knowledge and skill. The representative studies discussed here are experimental instructional interventions that focus on: (a) the acquisition of proceduralized skill, (b) the development of regulatory and monitoring strategies of comprehension, and (c) the acquisition of organized structures of knowledge. The programs' implications for learning theory are examined through an analysis of their theoretical backgrounds and the principles of learning that they reflect. The authors conclude by suggesting that studies of instruction can now address questions about the integration of the competences fostered separately by such programs and thereby contribute to the development of more comprehensive theories of the acquisition of knowledge and skill. Keywords:

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Abstract

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INTRODUCTION

Instructional psychology has become a vigorous part of the mainstream of research on human cognition and development. The 1980 Annual Review of Psychology documented the onset: "It is now difficult to draw a clear line between instructional psychology and the main body of basic research on complex cognitive processes" (Resnick 1981, p. 660). As we move toward the 1990s, the shape of the field is becoming apparent. Its contours are evident in the progress in research on three essential components of a theory of instruction (Glaser 1976): (a) description of competent performances (knowledge and skill) that we want students to acquire; (b) analysis of the initial state of knowledge and ability with which the learner begins instruction; and (c) explication of the process of learning, the transition from initial state to desired state that can be accomplished in instructional settings. These three components have not evolved to the same degree and differ in their influence on recent theory and experiment in instruction.

Over the past quarter of a century, cognitive research has focused primarily on the analysis of competence. Studies of memory, language, and problem solving have examined the nature of performance and the outcomes of learning and development. The advances in our understanding of competent performance, including recent studies of expertise, have had formative influence on instructional investigations. Research on the initial state of the learner has received attention more recently in developmental studies that document a priori constraints, principles, and strategies that govern children's learning, in investigations of naive theories and misconceptions that influence the attainment of new knowledge and skill, and in research on processes of intelligence and aptitude. In comparison to our knowledge of attained competences and expertise, the information accumulated on the initial state has only slightly influenced investigations of instruction, but should begin to assume a more significant role.[1] The least developed component of instructional theory is explication of the process of learning--a contrast indeed to behavioral psychology, where learning was of major concern.

Here we consider a set of seminal programs of instructional research in the context of this state of our knowledge. We focus on programs that are grounded in accumulated findings on one of three major aspects of competence: (a) the compiled, automatized, functional, and proceduralized knowledge characteristic of a well-developed cognitive skill; (b) the effective use of internalized self-regulatory control strategies for fostering comprehension; and (c) the structuring of knowledge for explanation and problem solving.

For each of the programs, we show how detailed cognitive task analysis has guided the specification of the objectives of instruction. We also attempt to explicate the principles, theory, and/or assumptions about learning and the principles that underlie the design of instruction. Thus our purpose is to describe the state of the art in applying the cognitive analysis of performance to the design of instruction and to consider current thinking about learning as conceptualized in investigations of instruction.

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[1] For fuller discussions of research on the initial state of knowledge and ability that the learner brings to instruction, see Carey (1985, 1986), Clement (1982), diSessa (1982), Gelman and Brown (1986), Gelman and Greeno (1988), Keil (1981, 1984), McCloskey (1983) McCloskey et al (1980), Nickerson et al (1985) and Sternberg (1985b, 1986).

COGNITIVE ANALYSIS OF PERFORMANCE, LEARNING, AND INSTRUCTION

Learning theory has been a central topic in psychology since its origins yet its research base, for the most part, has been analysis of relatively simple performances, and learning theorists generally have assumed that principles of learning would be extrapolated eventually to complex forms of learning. This assumption, with respect to instruction, has been strongest in the behavioral tradition spawned by Skinner. But increasingly, beginning in the 1970s (cf. Greeno 1980), questions were raised about the nature of what is learned: about the organization of knowledge, the characteristics of understanding, the knowledge and information processing requirements for solving problems, and the nature of the competences entailed in human performances requiring specific knowledge and skills resulting from long-term learning and extended experience. The attempts to answer these questions has brought the study of cognitive performance into prominence and temporarily set aside the study of the learning process.

The scientific decision to tackle performance was explicitly acknowledged by Newell and Simon in the 1972 book, Human Problem Solving.

> Turning to the performance-learning-development dimension, our emphasis on performance again represents a scientific bet. We recognize that what sort of information processing system a human becomes depends intimately on the way he develops. . . . Yet, acknowledging this, it still seems to us that we have too imperfect a view of the system's final nature to be able to make predictions from the development process to the characteristics of the structures it produces.
>
> The study of learning, if carried out with theoretical precision, must start with a model of a performing organism, so that one can represent, as learning, the changes in the model. . . .
>
> The study of learning takes its cue, then, from the nature of the performance system. If performance is not well understood, it is somewhat premature to study learning. . . . Both learning and development must then be

> incorporated in integral ways in the more complete and successful theory of human information processing that will emerge at a later stage in the development of our science. (p. 7-8)

Over the subsequent years, significant advances have been made in the analysis of puzzle-like laboratory problem-solving tasks, and, more recently, more complex ecologically valid performance has become the object of serious investigation in both cognitive psychology and artificial intelligence (Greeno & Simon 1988). Task analysis and knowledge-engineering approaches to the performance of experts have become prominent activities. In addition, the complex performances inherent in the school subject matters of reading, writing, mathematics, science, and social studies are being productively described (Glaser 1986).

Concepts that seem essential in the description of complex human behavior are now available. Most impressive is the pervasive influence of structures of knowledge as they interact with sophisticated processes of competent cognition (Feigenbaum 1988, Chi & Ceci 1987). The way knowledge is structured influences its accessibility, and knowledge representation determines understanding and influences problem solving (Greeno & Simon 1988, Gentner & Stevens 1983, Johnson-Laird 1983). We have learned also to appreciate the interplay of general and knowledge-derived processes (Glaser 1984, 1985, Sternberg 1985a), the development of automaticity and the relationships between unconscious and controlled processing (Shiffrin & Schneider 1977; Schneider 1985; Lesgold & Perfetti 1981), the efficiency and functional utility characteristic of a well-developed skill (Anderson 1981, 1987), and the significance of executive and self-regulatory processes, or metacognition (Brown et al 1983; Bransford et al 1986).

The phenomena captured by these concepts are essential features of the state of attainment that combine to produce the efficiency, judgment, seeming intuition, and outstanding abilities evident in competent performances (cf. Chi et al 1988). We know that, at various stages of learning, there exist different integrations of knowledge, different degrees of proceduralized and compiled skill, and differences in rapid access to memory--all of which shape the representations of tasks and differentiate levels of cognitive attainment. These differences signal advancing expertise or possible blockages in the course of learning. On the basis of this knowledge, dimensions are apparent along which changes in levels of performance occur. These dimensions have become focal objectives for instructional intervention.

Although advances in understanding the outcomes of acquired cognitive performance and, to a lesser degree, of the knowledge and skills brought to learning provide foundations for instructional theory, the study of the transition processes that a theory of learning must account for has been a depressed endeavor until recent years (see collection edited by Anderson 1981, Rumelhart & Norman 1978). Performance and memory are intimately intertwined in learning, but the difference in emphasis is critical. The acquisition of new declarative knowledge, development of a cognitive skill, organization of knowledge into more effective representations, and discovery and inference of new information are differentiated forms of learning and their characterization varies. Some learning can be characterized as simple accumulation of new information in memory, whereas in the acquisition of complex knowledge and skill over months and years, learning appears to involve qualitative restructuring and modification of schemata and has a more emergent quality.

No single set of assumptions or principles pervades the work of investigators who are conducting studies of instructional intervention, and there are, as yet, no major debates about general learning mechanisms. Rather, scientists are working toward principles of learning by bringing ideas from various areas to bear in different ways.

Attempts at instruction are based to a limited extent on explicitly stated theory, on general conceptions of the processes of acquisition for which specific learning mechanisms are unclear, and on observation of the practice of good teachers or tutors. What is common to all the approaches to instruction is grounding in an explicit cognitive task analysis; the objectives of instruction are based upon current knowledge of the characteristics of competent performance on a task. Less consistently, attention is given to shaping the instruction to accommodate the available relevant research on characteristics of the learner's initial state.

The investigators whose work we examine here focus on different forms of competence in separate domains of knowledge. At present, it is not possible to carry out an analysis that takes a particular area of performance and the forms of competence required and compare how different approaches attack a common task. The domains under investigation span medical diagnosis, reading comprehension, arithmetic skill, geometric proofs, and computer programming. These different domains interact with the researchers' conceptions of learning. We can describe, however, in a general way, representative programs in terms of their instructional objectives, assumptions about learner characteristics, processes of learning, and conditions for instruction. As we look toward the development of a theory of instruction, a primary concern is locating points of overlap and disjunction between prototypical work on the acquisition of proceduralized skill, the development of regulatory and monitoring strategies for comprehension and learning, and the acquisition of organized knowledge structures.

FUNCTIONAL, PROCEDURALIZED KNOWLEDGE AND SKILL

Studies of differences between experts' and novices' performances suggest that the course of knowledge acquisition proceeds from a declarative or propositional form to a compiled, procedural, condition-action form (Anderson 1983, Klahr 1984). Novices can know a principle, or a rule, or a specialized vocabulary without knowing the conditions of effective application. In contrast, when experts access knowledge, it is functional or bound to conditions of applicability. Moreover, experts' knowledge is closely tied to their conceptions of the goal structure of a problem space. Experts and novices may be equally competent at recalling specific items of information, but experts chunk these items in memory in cause and effect sequences that relate to the goals and subgoals of problem solution and use this information for further action. The progression from declarative knowledge to well-tuned functional knowledge is a significant dimension of developing competence.

A related aspect of competent performance is the speed of knowledge application. Experts are fast, even though human ability is limited in performing competing attention-demanding tasks (Shiffrin & Schneider 1977, Schneider 1985). This ability is particularly important in integrating basic and advanced components of skill. For example, in reading, as in medical diagnosis or in tennis, where attention must alternate between basic skills and higher levels of strategy and comprehension, automaticity is crucial for good performance. Even though the component processes may be well executed when performed separately, they may not be efficient enough to work together (Perfetti & Lesgold 1979). In the development of higher levels of proficiency, therefore, certain component skills need to become compiled and automatized so that conscious processing capacity can be devoted to higher levels of cognition as necessary. A dimension of acquired competence, then, is a high level of efficiency or automaticity required for appropriate subprocesses to have minimal interference effects, a level at which they can be integrated into total performance.

From Declarative Knowledge to a Procedural Skill

A widely discussed instructional program in which the learning objective is the acquisition of an efficient and functional cognitive skill has been developed at Carnegie Mellon University (CMU). A group led by John Anderson has designed computer tutoring programs for three complex well-defined skills: programming in LISP (Anderson et al 1984); generating geometry proofs (Anderson et al 1985); and solving algebraic equations (Lewis et al 1988). These programs are unique in their reliance on an explicit learning theory (Anderson 1983, 1987) and in their use of the instructional setting as a stage for systematically testing hypotheses about mechanisms of learning. Thus, besides its practical contribution to instruction, this work presents a model of the fruitful interaction between cognitive theory and instructional practice.

THEORETICAL BACKGROUND

The major learning mechanism posited by the ACT* theory is <u>knowledge compilation</u>, which accounts for the transition process from declarative knowledge, initially encoded from text or from teacher's instruction, into proceduralized use-oriented knowledge--converting "knowing what" into "knowing how." This theory makes the distinction between declarative and procedural knowledge fundamental. Declarative knowledge encoded in memory (such as the postulate Side-Angle-Side for proving triangles congruent) is assumed to be available for the development of skill. This knowledge is assumed to have been deposited in memory as a product of language comprehension, through reading a text or through oral instruction and lecture, without accompanying knowledge about its use and conditions of applicability. Procedural knowledge consists of sets of production rules (i.e., condition-action pairs) that define the skill in each domain.

The theory holds that effective and conditionalized knowledge of procedures can be acquired only through use of the declarative knowledge in solving actual problems. First, during solution, declarative knowledge is drawn on in applying general problem-solving processes--weak methods, such as means-ends search, hill climbing, or analogy to an example. The subsequent process of knowledge compilation creates efficient domain-specific productions from the trace of the initial problem-solving episode. Compilation consists of two major mechanisms, proceduralization and composition. Proceduralization is a result of comparing the problem state before and after generating the solution and creating a production rule--the building block of the domain-specific skill. Composition, analogous to chunking, is the result of collapsing a sequence of productions into a single production that has the same effect as the components of the sequence. Composition reflects meaningful cognitive contingencies as constrained by a hierarchical goal structure for the solution of the problem. Finally, the various productions accumulate strength as a result of practice with successful applications (much as in the strengthening of associative bonds).

The initial interpretative process of solving problems using declarative knowledge by means of weak methods places a high demand on conscious cognitive processing. Knowledge compilation results in automaticity of application and in proficient execution of previously acquired knowledge. It frees the working memory, leaving more capacity for the processing of new knowledge. It also eliminates the relatively undirected search that characterizes early performance. The process of knowledge compilation is assumed to be an automatic learning mechanism, and the major instructional principles involved in the design of the tutors derive from theoretical assumptions about the process.

INSTRUCTIONAL PRINCIPLES

The three tutoring programs build on detailed and explicit analyses of both performance and learning. The ACT* theory explicates how students actually execute the skill that is to be taught. This knowledge comprises a performance model that consists of a set of all the correct and incorrect production rules for performing the skill. The model corresponds to the performance of an ideal student and to buggy variations of the ideal student's rules at various stages of skill development and not to a fully blown expert system. The learner's actual performance is compared in real time to the rules in the model, and the tutoring system tries to keep the student on a correct solution path. The performance model is accompanied by a learning model consisting of a set of assumptions about how the student's knowledge state changes after each step in solving a problem. Using parameters derived from the ACT* theory, the student's history of correct and incorrect application of productions provides an updated probabilistic estimate of the availability and the strength of the productions comprising the skill (similar to response probability in statistical learning theory models for vocabulary instruction [Atkinson, 1972]). Trackings of changes across problems enables the tutor to select problems appropriate to the student's knowledge state in order to optimize learning. Within this general model tracing paradigm, instruction is guided by several principles.

Learning via problem solving Learning occurs by doing, by interpretation of declarative knowledge via problem solving. A given problem provides a set of applicability conditions relevant to problem-solving goals. It is assumed that in order for the student to retrieve the learned information in solving other problems, he or she initially has to encode it in a similar problem-solving context during studying. The CMU group advocates shortening preliminary instructional texts, refraining from elaborated explanations, and focusing on procedural information and on actual problem solving as soon as possible. Textual instructions should be carefully crafted to maximize correct encoding, but the inevitable misunderstandings should be corrected during problem solving.

<u>**An ideal problem-solving structure for the domain**</u> Each tutor communicates a particular problem-solving structure best suited to the domain. Carrying out geometry proofs, for example, requires backward and forward search for logical inferences between the givens and what is to be proved. To explicate the search, the tutor uses proof graphs. A proof is completed when a set of subgoals reached by backward inferences from the to-be-proven statement is actually linked with a set of subgoals reached by forward inferences from the problem's givens. The proof graphs represent the actual problem-solving space and explicate the search process for constructing a geometry proof. In contrast, constructing a program in LISP is a design activity and has a very different structure, that of problem decomposition. A programming goal has to be decomposed into subgoals until goals are reached that can be achieved with specific code. For instruction, the LISP tutor provides a template organized in a hierarchical goal structure with slots that the student must fill.

<u>**Problem specification and immediate error correction**</u> Knowledge compilation and the strengthening of acquired productions result from successful applications of the productions. To ensure maximal correct performance, the tutor monitors the student's learning closely by selecting problems and by displaying and constraining the solution steps. The selection of problems is guided by a <u>mastery model</u>--the tutor presents problems involving new rules only when the student has attained a certain threshold level of competence on the current rules. Appropriate additional problems and accompanying instructions provide practice on those production rules that are diagnosed as weak or missing in the student's knowledge state.

During problem solving, the tutor traces the student's performance by matching it to the system's model for a correct solution and intervenes as soon as the student deviates from one of the possible correct solution paths. Errors are corrected immediately, both to avoid lengthy exploration of erroneous paths and to assign blame at actual decision points. The feedback consists of identifying errors and suggesting how to proceed. A complete or a partial solution may be offered, but, in keeping with the principle of learning by doing, wherever possible, the student is required to produce the correct solution.

Minimization of working memory load Because acquisition of new knowledge places burdens on memory, the tutoring environments aim to minimize the cognitive load. They implement all components accessory to the target skill. For example, when the skill is writing code, the editor of the LISP tutor takes care of such syntactic details as supplying parentheses or the structure of a function. The tutors also maintain relevant contextual information on the screen; for example, the LISP tutor displays the current goal stack to support the student's memory of solution steps.

OVERVIEW AND ANALYSIS

It is worthwhile to consider the scope of the instructional theory and of the learning principles involved in these tutors. First, they are not claimed to be appropriate for learning objectives other than acquisition of proceduralized skill. Furthermore, the only learning mechanism that guides the current tutors is the automatic process of knowledge compilation. However, *other more* conscious inferential mechanisms might be involved. Identifying such mechanisms could lead to different instructional recommendations. For example, as Anderson (1987) has pointed out, analogical problem solving is fundamental in the skill acquisition domains that the CMU group has been studying. In the course of learning, students resort to examples from the same or another domain that are retrieved from prior experience. The process by which analogous experience helps students solve new problems and its implications for instruction are not yet specified. Also, the present view of skill acquisition is minimally adaptive to differences in previous knowledge. Students are assumed to enter the learning situation with only limited declarative information and with an intelligent person's set of general problem-solving heuristics. This approach might be appropriate for achieving elementary levels of skill proficiency in well-structured tasks, such as learning the syntax and semantics of a new programming language. In more complex reasoning tasks and for more sophisticated expertise (e.g., program planning and debugging [Soloway & Johnson 1984]), consideration of understanding and organization of the declarative knowledge may be essential.

Although successfully fostering skill proficiency is, in itself, an important goal, the focus on an automatic learning process of skill acquisition may be further guided by the assumption that acquisition of efficient skill at each level of expertise is a necessary facilitating condition for subsequent depth of understanding and reasoning. The view that understanding and planning ability will emerge as by-products of the basic learning mechanisms for skill acquisitions might also be involved. This conceptualization of learning is shared by others (e.g., Anzai & Simon 1979, Neches 1984, Klahr 1984, Siegler 1989) who stress learning by doing and focus on the procedural efficiency achieved with practice. They believe that proceduralization of knowledge results in qualitative changes in knowledge structure and in changes of choice of cognitive strategies. Siegler (1989) has suggested that extensive practice on such skills as addition, subtraction, reading, and time telling leads to changes in response distributions that later result in switches of strategy choice (from calculation to retrieval). The theoretical implication is that major metacognitive changes are an unconscious byproduct of highly practiced successful performance. Of course, others, like those whose work we discuss later, would disagree with such an exclusive focus on skill acquisition. How much learning can be explained by mechanisms such as knowledge compilation and how skill efficiency relates to other aspects of expertise remain open empirical questions.

Anderson views learning as a domain-independent and relatively simple process. Disparities between domains result from different organization of productions and from differences in the initial usefulness of general heuristics. Because the instructional principles in the tutoring programs derive from a general theory of skill acquisition. Anderson holds that the pedagogical strategies can be decoupled from the domain knowledge. His theory of human skill acquisition reflects belief in generalizable basic learning principles, so the most effective tutoring strategy simply would optimize use of these learning principles (Anderson, Boyle, Corbett, & Lewis, 1988). The assumed generality of the underlying learning theory is to be kept in mind as we review other instructional approaches.

Anderson's theory and work are continuous, to an appreciable extent, with the learning tradition in experimental psychology in which emphasis is placed on the transition of a skill from an intermediate associative phase to a final autonomous phase (Fitts 1962, Fitts & Posner 1967). In that tradition, the component subroutines are acquired and integrated in the intermediate phase, and they become less subject to cognitive control and environmental interference and require less conscious processing in the final phase. In addition, the close control of the learning process, the immediate feedback during problem solving, the focus on minimizing errors, and the gradual approximation to experts' behavior by accumulation of separate parts of the skill are reminiscent of Skinnerian shaping and successive approximation and of the early variations of programmed instruction. The cognitive sophistication of Anderson's theory, however, requires also organizing the productions according to the problem-solving structure of goals and subgoals, as well as introducing the intelligent component of the instructional system to trace the student's knowledge and performance.

SELF-REGULATORY SKILLS AND PERFORMANCE CONTROL STRATEGIES

Studies of expert performance, work in developmental psychology, and AI problem-solving models reveal the role that self-regulatory or control strategies play in competent performance. The experience of experts enables them to develop executive skills for monitoring performance; they rapidly check their work on a problem, accurately judge its difficulty, apportion their time, assess their progress, and predict the outcomes of their performance (Simon & Simon 1978, Larkin et al 1980, Brown 1978, Miyake & Norman 1979, Chi et al 1982). These self-regulatory skills vary in individuals and appear to be less developed in those with performance difficulties. Superior monitoring skills both reflect the efficient representational skills of experts in their domains and contribute to the utility of their knowledge. Because knowledge of a rule or procedure is enhanced when one can oversee its applicability and monitor its use, self-regulatory skills are important outcomes of learning.

The investigations of developmental psychologists support the view that the growth of metacognition is a significant dimension of evolving cognitive skills from childhood onward. The emergence of metacognitive processes has been examined in work on children's knowledge of their own abilities (Flavell et al 1970, Brown et al 1983, Bransford et al 1986), their comprehension monitoring (Markman 1985), their allocation of effort and attention, as well as their editing and error correction during problem solving.

In work on artificial intelligence, the design of problem-solving systems requires central strategies for deciding what operator to apply and where and when to apply it, as well as a database describing the task domain and a set of operators to manipulate the database (Barr & Feigenbaum 1981). The control strategies define planning processes that are implemented in a hierarchical database structure or that can be more opportunistic and applied to local decisions as a plan develops. Thus, competent problem solving can be both plan and event driven. In the design of computer models of cognition, researchers have either assumed that a separation between resources and control is not essential, as it is in production system models, or made a distinction between the two, not only as a programming convenience, but as a characterization of human cognitive processes. This distinction becomes especially important in learning and instruction when the learner's strategies for accessing information cannot be assumed to be well developed. Thus, many lines of work force consideration of the development of executive control performances as an important dimension of learning and instruction.

Internalizing Self-Regulatory Strategies for Comprehension

Instructional programs in reading, writing, and mathematics designed to foster the development of self-regulatory skills through supportive modeling of task performance are a major area of research (Collins et al 1988). A program for reading comprehension developed by Brown and Palincsar (1984, 1988) has received sustained analysis and been widely cited. Students in this program acquire specific knowledge and also learn a set of strategies for explicating, elaborating, and monitoring their understanding that is necessary for independent learning. The knowledge acquisition strategies they learn in working on a specific text are not acquired as decontextualized skills, but as skills that are instrumental in achieving domain knowledge and understanding. The instructional procedure, called Reciprocal Teaching--reciprocal in the sense that teacher and a group of students take turns in leading the procedure--specifies strategies for comprehending and remembering text content. Its three major components are (a) instruction and practice with strategies that enable students to monitor their understanding; (b) provision, initially by a teacher, of an expert model of metacognitive processes; and (c) a social setting that enables joint negotiation for understanding. The last two components appear to be ingredients in the success of apprenticeship learning in natural settings (cf. Greenfield 1984, Lave 1977, Lave et al 1984).

THEORETICAL BACKGROUND

Two general conceptions in developmental psychology underlie the notions of learning that influence this approach. One is that conceptual change is self-directed, in the sense that humans are intrinsically motivated to understand the world around them. Internal structures, principles, or constraints predispose learners to search for causes and explain events to extend their knowledge. Equipped with initial knowledge (facts, concepts, and rules), the learner tries to impose a causal explanation on the situation at hand. Failure to generate an explanation creates a conflict or dissatisfaction with the existing state of knowledge. Such a conflict triggers mental experimentation (Gelman & Brown 1986) to seek data to test and modify the current explanations. Inquiry proceeds until the learner is able to generate a satisfactory explanation. This new explanation, both the result and the process of generation, is assimilated through restructuring or replacing the initial knowledge organization.

The second general conception derives from theories that emphasize learning's social genesis. Conceptual development in children involves internalizing cognitive activities originally experienced in social settings. Thus, the process of generating explanations, whether enacted by the learner himself, with the help of others, or even completely by others, is believed to be internalized gradually. Internalization (after both Piaget [1926] and Vygotsky [1978] is considered to be a key mechanism of learning. (Brown points out that detailed explication of this mechanism and of the processes involved in assimilation and restructuring have yet to receive theoretical and empirical analysis.)

INSTRUCTIONAL PRINCIPLES

Strategies for monitoring comprehension The program focuses on four strategies: questioning, or posing questions about the main content of a paragraph; clarifying, or attempting to resolve misunderstandings; summarizing, or reviewing the gist of the text; and predicting, or anticipating text development. These activities serve to improve comprehension by signaling and monitoring progress toward understanding. Inability to summarize a section, for example, indicates comprehension failure and initiates efforts to clarify the problematic aspect of the text. The application of these strategies structures and constrains the discussion. Thus, the dialogue leader, usually first the teacher and later the students, begins by asking a question on the main content and invites clarifications, then summarizes the gist, and, finally, asks for predictions about future content.

The teacher as model and coach The role of the adult teacher is adapted from principles of guided learning, especially those of expert scaffolding (cf. Bruner 1978, Wood 1980) and Socratic tutorial dialogues (cf. Collins & Stevens 1982, Davis 1966). First, he or she models mature comprehension activities by explicating use of the target strategies. Students can observe the teacher retelling content in her own words, asking what something means, or posing questions about main points. Watching the teacher model, students become familiar with the strategies and with their utility for penetrating a text to extract central facts or themes. Also, they learn that understanding involves active construction of meaning.

After modeling the techniques, the teacher transfers the leading role to one of the students and assumes the role of a coach, ready to intervene or not, as necessary. For example, when a student is unable to generate a question, the teacher may suggest the content and/or the form of a possible question (e.g., what would be a good question about the pit vipers that starts with the word why?), or, if necessary, pose the correct question and ask the student to repeat it. When the learner manages the task on his own, the teacher fades out her intervention and primarily supports the ongoing discussion. (The metaphor for such coaching, a scaffold, captures the idea of an adjustable temporary support that can be removed when no longer necessary.)

Shared responsibility for the task The Vygotskian concept (1978) of thinking as essentially the individual's re-enactment of the cognitive processes that were originally experienced in society underlies the program's focus on group learning. The program's provisions for the learning group are adapted from studies that have pointed out the motivational and cognitive variables involved in shared responsibility for thinking that enhance learning in group settings. (See Brown & Palincsar [1988] for a review of relevant studies.) Cooperative learning provides social support, encouragement, and rewards for individual efforts. From a cognitive perspective, a group serves several additional roles. First, it extends the locus of metacognitive activity by providing triggers for cognitive dissatisfaction outside the individual. An audience monitors individual thinking, opinions, and beliefs, and can elicit explanations of how and why that clarify points of difficulty. The learner's exposure to alternative points of view can also challenge his initial understanding. In addition, with the help of a teacher who provides expert scaffolding, the collaborative group maintains a mature version of a target task. Overall, by sharing it, a complex task is made more manageable without simplifying the task itself. The group achieves understanding until such time as its members have acquired the skills themselves. Each learner contributes what she can and gains from the contributions of those more expert. The Reciprocal Teaching method, with its combination of group discussion and scaffolded instruction, creates a zone of proximal development where learners perform within their range of competence while being assisted in realizing their potential levels of higher performance (Vygotsky 1978).

In keeping with the goal-directedness, integrated character, and conditionalized nature of competent performance, programs like this one encourage teaching in the context of problem-solving situations that approximate mature practice. Also, they emphasize comprehension and meaningful outcomes as objectives of learning via the use of cognitive strategies. The learning strategies involved are seen as instrumental to acquisition of content and skill in a domain of knowledge. The strategies employed are not claimed to be heuristics or processes comprising generalized, all-purpose skills of intelligence and general learning ability. Rather, they are designed for and tailored to the specific domain being taught and are learned and practiced while being used for solving problems in that domain. Indeed, within the same general approach, different sets of specific strategies are suggested in programs for teaching other domains.

Related Work A program of procedural facilitation for teaching writing composition shares many features with Reciprocal Teaching (Scardamalia et al 1984). The method involves explicit prompts aimed at supporting student's adoption of the metacognitive activities embedded in sophisticated writing strategies. The prompts help students identify goals, generate new ideas, improve and elaborate existing ideas, and strive for their cohesion. Where students in Reciprocal Teaching take turns in leading the discussion, students in the procedural facilitation program take turns presenting to the group their ideas and their use of prompts in planning to write. The teacher also models the procedures. Thus, this program too involves modeling, scaffolding, and turn taking designed to externalize mental events in a collaborative context.

A program designed by Alan Schoenfeld teaches heuristic methods for mathematical problem solving to college students (1983, 1985, 1988), methods derived, to some extent, from the problem-solving heuristics of Polya (1957). Schoenfeld's program adopts methods similar to Reciprocal Teaching and procedural facilitation. He teaches and demonstrates control or managerial strategies and makes explicit such processes as generating alternative courses of action, evaluating which course one will be able to carry out and whether it can be managed in the time available, and assessing one's progress. Again, elements of modeling, coaching, and scaffolding, as well as collective problem solving and class and small group discussions are employed. Gradually, students come to ask self-regulatory questions themselves as the teacher fades out. In an interesting variant of teaching tactics, at the end of each of the problem-solving sessions, students and teacher alternate in summarizing a solution episode by analyzing what they did and why. Those recapitulations highlight the generalizable features of the critical decisions and actions and focus on strategic levels rather than on the specifics of solution.

Furthermore, Schoenfeld directly confronts the issue of imparting an appropriate belief system about the interpretive nature of mathematical problem solving. During the process of learning mathematics, students begin to realize that searches often come to dead ends; exploration of possible heuristics and different paths does not guarantee solution. He challenges his students to find difficult problems for him to solve so they can observe his own struggles and floundering, which legitimate students' floundering as well. Students begin to realize that mathematics requires not merely recognizing principles, nor merely applying procedures, but, rather, a creative interpretive process of exploration and reasoning.

OVERVIEW AND ANALYSIS

In these programs, students do learn to apply the appropriate set of monitoring strategies, and there is improvement in domain skill. The designers, however, have the more ambitious objective in mind that students develop particular attitudes toward their own learning. While learning to apply various cognitive control strategies, students are expected to acquire a conception of learning and problem solving in which skilled cognitive strategies guide their activities. An important question is to what extent students can generalize this attitude and transfer the strategies to other situations and across domains.

It is interesting to note the critical shared assumption in these programs that thinking skills are best cultivated in the context of the acquisition of domain knowledge. The shift in cognitive science and AI from modeling general heuristics to specifying uses of knowledge and the findings on the knowledge-derived processes of expertise give warrant to that assumption. We cannot consider here the range of current activity on teaching the processes of general intellectual ability and general problem-solving and thinking skills to support learning (cf. Chipman et al 1985, Segal et al 1985, Glaser 1984, Resnick 1987a, Bransford et al 1986, Sternberg 1986, Nickerson et al 1985). It is our judgment that, at present, the research on general intellectual abilities, as they relate to instruction, need further investigation. As our concluding discussion indicates, however, it is possible to anticipate the eventual synthesis of these findings with detailed analysis of specific domain learning.

There are certain similarities among the instructional principles employed in this group of programs and those in the tutors for procedural skills. For example, in the tutors developed by the CMU group, students are kept on a correct solution path and are not permitted to flounder. When a student chooses an incorrect move, the tutor intervenes to identify the error and promptly suggests an alternative move if the student is off track. When the tutor identifies a bigger problem, it intervenes with several examples. Similarly, in the Reciprocal Teaching method, Brown and Palinscar stress that the teacher keeps the discussion focused on the content and closely monitors the student leaders, providing feedback or resuming control as necessary. There are further similarities with respect to successive approximation, to gradual fading of support, and to explicit modeling.

However, these two sets of programs present very different views of the learner. The knowledge compilation approach sees the learner as striving for efficiency in performing a well-defined skill; the metacognitive programs conceive of the learner as motivated to explore and seek explanations. These two views and the instructional environments they prescribe might be taken as complementary: the first would be appropriate for novices' acquisition of basic skills, whereas the latter would be appropriate for advanced students' acquisition of strategic skills in the service of understanding. Nevertheless, the two conceptualizations of the learner and of the process are not easily bridged, regardless of choice of objectives or domains. Those who adhere to the metacognitive approach fault current modes of schooling because students often acquire skills mechanically; although efficient, these skills remain as inert knowledge that is not easily accessible in different situations. So we can expect expanding research on metacognitive approaches to the acquisition of basic skills. The interesting issue is whether the extensive practice required to attain reasonable efficiency and automaticity in basic procedural skills might be achieved not only in highly structured environments in which students practice subcomponent procedures, but also in the context of the mature task format of a reciprocally supportive cooperative learning group.

Finally, it is worth repeating that, although the various programs for teaching self-monitoring skills are based on a detailed analysis of strategies used by successful readers, writers, and mathematicians, the assumed learning mechanisms of internalization, assimilation, and restructuring are, as yet, little understood.

KNOWLEDGE ORGANIZATION AND STRUCTURE

As competence is attained, elements of knowledge become increasingly interconnected so that proficient individuals access coherent chunks of information. Beginners' knowledge of a domain is spotty, consisting of isolated definitions and superficial understandings of central terms and concepts. As proficiency develops, these items become structured and are integrated with past organizations of knowledge so that they are retrieved from memory rapidly and in larger units (cf. Rumelhart & Norman 1978). The exceptional memory retrieval of experts in a domain is based on the structured content of stored information (Ericsson & Staszewski 1988). These organized structures of knowledge are referred to as schemata (Rumelhart, 1980). Such structures evolve and are modified and elaborated to facilitate more advanced thinking, and they enable forms of representation that are correlated with the ability to solve problems.

It is now well known that novices work on the basis of the surface features of a problem and that more proficient individuals make inferences, identify principles, and envision mental models that subsume surface structure. In research by Chi, Glaser, and Rees (1982), novices and experts were asked to group mechanics problems. Novices put together problems that involved pulleys, inclined planes, and so on. Experts, in contrast, grouped those solvable with Newton's laws of motion, on the one hand, and those solvable using energy equations, on the other. The expert apparently organizes his or her knowledge in terms of schemata not salient to the novice, as is apparent in analyses of the solution processes. Larkin, McDermott, Simon, and Simon (1980) have shown that when solving mechanics problems, novices use painstaking means-end analysis, working backward from the unknown with equations that they hope are relevant to the problem. Experts, in contrast, apply correct equations in a forward direction, indicating that they have a solution plan in place before they begin. Again, schemata appear to enable experts to grasp the structure of problems and then proceed with quantitative solutions in a way that novices cannot. Such representational ability for fast recognition and perception of underlying principles and patterns and its use in problem solving has been replicated in a variety of domains (e.g., Chi et al 1988). The pre-eminence of expert pattern recognition is such that the expert virtually sees a different problem than the novice (Charness 1988).

A related line of current research is concerned with qualitative reasoning in the use of mental models that people construct of situations and systems they attempt to understand (Gentner & Stevens 1983, Johnson-Laird 1983). These runnable mental simulations are built, used, and modified as proficiency is acquired. The use of models reveals important aspects of inferencing that facilitates problem solving and comprehension. Access to mental models in familiar domains of knowledge can foster reasoning that is not present in abstract logical problems (Falmagne 1980, Johnson-Laird 1982, 1983). Problem solving is differentially effective depending on the type of mental model employed (Gentner & Gentner 1983). Within an AI framework, Brown and deKleer (1985) and Forbus (1985) propose formalizations of causal and qualitative models people use when reasoning about physical processes. Within cognitive psychology, Stevens and Collins (1980) have described multiple mental models that students hold for explaining such natural processes as rainfall, and they suggest that learning is a process of adding, replacing, deleting, generalizing, and differentiating parts of the model and of mapping between different models. In related research, Collins and Gentner (1987) have described the use of analogies and their integration in constructing various component models for the process of evaporation. AI and psychological approaches have been combined by Forbus and Gentner (1986), who suggest a progression of mental models in which causal and qualitative models are necessary to the development of expert-like quantitative mathematical models.

In general, structured knowledge enables inference capabilities, assists in the elaboration of new information, and enhances retrieval. It provides potential links between stored knowledge and incoming information, which facilitate learning and problem solving. Two lines of instructional work serve here as examples of programs that are guided by research on structured knowledge. The first has evolved in the AI tradition of knowledge engineering and the construction of expert systems. Its central aim is imparting to the learner the knowledge characteristic of well-developed expertise. The second line of work is newer and originates from research on qualitative reasoning and on the evolution of mental models.

Structuring Knowledge for Problem Solving

The analysis of information structures in the form of knowledge networks is documented as an approach to instruction beginning with Carbonell and Collins' (1973) SCHOLAR program. In this so-called mixed-initiative Socratic tutoring program, the system and the student initiate conversation by asking questions; knowledge about the domain being tutored is represented in a semantic network. Since that time, with the growth of AI and the development of intelligent computer tutors, increasingly advanced attempts at explicit tutoring in the context of expert knowledge structures has forced us to investigate the kinds of knowledge representation that facilitate students' interaction with the domain expert or with the expert teacher.

The GUIDON project, led by Clancey (1986), is a carefully documented attempt to use a model of expert knowledge to design an intelligent tutoring system. The learning objective is the acquisition of a well-organized body of knowledge in the complex domain of medical diagnosis and of the heuristic strategies required to use this knowledge for practical problem solving. The initial base of expertise, modeled in the system's forebearer, MYCIN (Shortliffe 1976), consisted of knowledge in the compiled form that characterizes the expert problem solver. Although excellent in its performance capabilities, it lacked the explicit organization and reasoning strategies necessary for tutoring. This additional expertise was modeled from the explanations generated by a good physician-teacher. Accordingly, the base of expertise was reconfigured (NEOMYCIN, Clancey & Letsinger 1984) into a structure of knowledge that represented the expert's principled understanding of the domain, as well as a large number of problem-solving routines in decompiled form. This new knowledge base was organized into categories of general principles that underlie domain knowledge, definitional and taxonomic relations, causal relations, and heuristic rules and strategies. The reasoning strategies involved revolve around the management of hypotheses--grouping hypotheses into more general cases, refining them into special cases, differentiating them, and so forth. Within the expert model for medical diagnosis, these strategies are represented as general reasoning processes of inference that are separated from the domain knowledge.

The next step in the evolution of the project was construction of a domain-independent expert system that builds on the reasoning strategies underlying a class of problem-solving tasks demanding heuristic classification (HERACLES, Clancey 1984a, 1985). In this system, a predetermined taxonomy is used to relate features of the data to descriptions of candidate categories. The system is general enough to fit such domains as electronic troubleshooting, where one has to recognize known malfunctions from symptoms, as well as other forms of problem solving where a fixed set of solution methods must be selected relevant to specific situations. This evolution in the conceptualization of expert knowledge, from a compiled set of domain-specific rules to a set of general strategies that operate on an organized body of knowledge, was accompanied by a change in the instructional objective and in the conception of the learning process. In recent developments (GUIDON 2, Clancey 1984b), the instructional objective is not only expertise in medical diagnosis, but also the learning process by which one actively constructs an organized body of functional knowledge. Accordingly, the instructional strategy is no longer to present information to the learner in order to fill a knowledge base; rather, it is to provide an environment for active and self-directed learning in the context of explicit expert knowledge.

THEORETICAL BACKGROUND

The learning process in this approach is characterized as "failure-driven, explanation-based learning for nonformal domains" (Clancey 1987, p. 27). Learning is based on detection and explanation of problem-solving failures. The failure detection as well as the suggested repairs result from the learner's efforts to apply existing partial and incomplete schema to the solution of a specific problem. The learning objective is to acquire new knowledge in the context of generating a causal solution linking conclusions to findings. This conception of learning emphasizes the active role of learners, who direct their own learning by generating plausible conjectures about missing knowledge and by posing focused questions to an expert teacher.

More specifically, the learner is assumed to have background knowledge about the domain to be taught. For instruction with the medical tutor, students' knowledge of fundamental medical terms and concepts and disease processes is assumed. Equipped with this initial knowledge, the learner is introduced to the expert's knowledge representation as organized hierarchically and taxonomically. The learner is also introduced to a set of general heuristic inference rules for grouping, differentiating, and testing hypotheses. To foster generality, these rules are expressed in generic language rather than in terms of diseases and symptoms. Thus, the classifications of disease and symptom type, cause, and location are treated in terms of a general diagnostic reasoning process of clarifying findings, providing data to discriminate between hypotheses, and so on.

The student's prior knowledge about disease processes, together with her initial understanding of the expert knowledge representation and inference procedures for classification, constitute a partial schema (or an incomplete general theory) of the diagnostic relations. This schema guides the student's inquiry to a situation specific model for a particular case. Given a case, the student acts as a diagnostician, proposing hypotheses about the nature of the disease and gathering data to guide further hypothesis generation and testing. The process of diagnosis builds a coherent argument that causally relates all the findings or symptoms to be explained to the processes that brought them about. The system displays the student's solution as a progressive extension of a graph (similar to the graph representation for constructing a geometry proof in Anderson's tutor) that links conclusions to findings, until the graph represents all the relations for the case.

The student herself directs the diagnosis by implementing inference strategies and by interpreting the evolving solution. Learning is driven by failure; the student may be unable to test or to refine a hypothesis, to explain or justify a finding, or to discriminate between two or more hypotheses that explain the same findings. After detecting the failure, which is indicated by the inability to generate a link in the solution graph, the student has to generate possible repairs by reasoning about the additional domain knowledge that, if available, might have prevented the failure. She then articulates the nature of the deficiency by posing a specific question to the system. If the information proves sufficient to generate the desired link, the student updates her knowledge base accordingly.

INSTRUCTIONAL PRINCIPLES

Because the methodology of the knowledge-engineering approach required shaping instruction around an expert model for a domain, it demanded a careful analysis of domain structure and decompilation of expert knowledge. This analysis was followed by construction of a validated model of expertise, which performs the tasks the student is to learn. The instructional system was developed as a separate expert system; ideally, it can be used with any domain of the heuristic classification type by adapting it to the nature of the domain. The following instructional principles are embedded in the approach.

An articulated expert model as an object of study The student has the opportunity to explore the expert's knowledge organization by browsing through its taxonomies and tables. She can see the expert's reasoning during problem solving and can pose questions or request explanation at any time. An articulated representation of the expert's decompiled knowledge and a simulation of the correct problem-solving process are available to study and emulate as the student constructs her own understanding of the domain.

Explication of the reasoning process The student is explicitly introduced to the nature of the reasoning process by observing the system diagnosing specific cases using strategies of heuristic classification (The GUIDON WATCH system, Richer & Clancey 1985). Furthermore, students can observe the specific problem representation (a connected graph) and the appropriate vocabulary for applying the strategies and for requesting information. Through the use of a domain-independent representation of reasoning and of domain-independent terminology, it is hypothesized that students will learn strategies applicable to other domains as well.

Construction of a situation-specific model The student is presented with a realistic problem-solving context that forces the construction of a situation-specific model describing the processes by which the problem features were produced. Because the situation model is intimately tied to the goal of solving a problem, it provides an ideal environment for detecting failures and for hypothesizing and testing new facts. What the student learns is based on acquiring knowledge that arises in solving a particular problem and is directly related to the inference procedure being applied.

Self-directed learning The learner controls and directs the learning process. First, in generating a situation-specific model in the form of a connected graph, the learner herself can detect a failure. Second, in attempting to repair a failure, the student has to determine what information is needed and to formulate a specific question for the expert teacher. A basic assumption is that learning will be more efficient if the student determines what she needs to know, rather than if the teacher builds and tests a model of her current knowledge.

OVERVIEW AND ANALYSIS

The notion of learning that drives the program focuses on the acquisition of new domain knowledge and inferencing skills, not on the processes of knowledge chunking and compilation. In a sense, the two approaches could be conceived as complementary, assuming that, as the learner acquires new knowledge while diagnosing consecutive cases, it becomes proceduralized and the learner becomes more efficient in applying diagnostic skills. The difference in focus, however, is accompanied by disparate conceptions of the learning process and leads to different instructional principles. Although, as in the knowledge compilation programs, GUIDON 2 assumes that learners begin their problem solving with an initial body of declarative knowledge, the latter strongly implicates the initial organization of that knowledge to serve as a partial schema. This schema allows mindful application of reasoning strategies for locating failures and developing a more coherent representation. GUIDON 2 also focuses explicitly on the acquisition of new declarative knowledge through the conscious processes of error detection and repair. The minimization of errors suggested in the theory of automatic knowledge compilation is a sharp contrast.

In GUIDON 2, there is no control or intervention from the tutor other than responding to the student's requests, no shaping or successive approximation. The programs that focus on teaching metacognitive strategies share with GUIDON 2 the conception of learning as failure driven and motivated by the desire to resolve conflict and to construct an explanation using a set of executive strategies. But the metacognitive skills groups, those working with children as well as adults, rely on careful shaping of learning strategies by the teacher. In implementing his program, Clancey may find that it is insufficient for a student to observe the system in order to learn the various heuristic strategies and that more direct intervention is needed from the tutor.

Although Clancey makes assumptions about learning, the instruction is based principally on the analysis of competent performance. His most recent conceptualization (Clancey 1987) of the learning process builds on the analogy between how a knowledge engineer probes the human expert to model expertise and how an ideal learner might observe and interact with expert performance. He plans to develop a learning model of the probing tactics and to design a tutorial program that conveys them to the student. The learner then will be able to emulate the model's efficient learning performance, and the tutorial program will be able to make decisions for guiding the ongoing learning based on the model. The rationale behind this plan is that it is not sufficient to analyze only the target knowledge that comprises expertise; it is necessary also to understand knowledge acquisition, to carefully analyze both the various strategies used to observe and to interrogate the expert and the knowledge updating and restructuring that occur during learning.

It is interesting to compare this approach to the model tracing approach in Anderson's tutors for procedural knowledge. There, the model of the learning process is used by the tutor for tracing and correcting the student's solution path, but the model's production rules are not presented to the student. Because Clancey deals with learning that requires conscious choice of strategies, conscious self-monitoring of understanding, and systematic interrogation of the expert's knowledge, he intends to present students with an explicit learning model. This conception is similar to that in the apprenticeship programs, which stress the exposition of explicit learning strategies. Emphasizing conscious strategy use may be important to the acquisition of new knowledge, as well as to the creation of a repertoire of backup strategies for future recovery from failure and for coping with unfamiliar situations.

It is interesting also to discuss the work on GUIDON 2 with respect to generality and transferability. First, Clancey points out that he adopts a specific representation of medical knowledge that is tailored to diagnosis. He presents an assimilation model of learning that does not assume any representational changes to the knowledge base. Thus, knowledge is acquired only in the form suitable for diagnosis, not for treatment, say, or research. Accordingly, Clancey does not expect transfer of the knowledge per se. However, because the skill of diagnosis has a structure similar to other tasks involving heuristic classification, he believes that the general reasoning involved can be transferred. To stress its generality, he uses general schema for heuristic classification, but it is as yet unclear whether, indeed, students will acquire such schema through experience in a single domain. (Clancey [1987] points out that an experienced knowledge engineer, who serves as his model of a good learner, typically develops his expertise by interrogating expert's knowledge in several domains.) Clancey's conception of generality and transfer is compatible with Anderson's (1987). Anderson compares the skill of proof evaluation to the skill of proof generation in geometry; although they are based on the same declarative knowledge, the production rules do not overlap. According to ACT* theory, transfer will not occur between two different skills based only on the same declarative knowledge. Positive transfer between skills, however, may occur to the extent that they involve the same hierarchical goal structure controlling the behavior. (Singley & Anderson, unpublished manuscript).

Progression of Qualitative Mental Models

Instructional work that stems from research on mental models represents an effort to teach understanding of a domain by utilizing possible transitions between the intuitive understanding developed as a result of informal experience and expert conceptualizations. The program developed by White and Frederiksen (1986) for teaching trouble shooting in electric circuits focuses on qualitative causal reasoning as a basis for conceptual understanding. White and Frederiksen assume that expert's knowledge is organized in coordinated mental models, and, accordingly, they lead the learner through a progression from simple to advanced models. Each mental model incorporates declarative and procedural knowledge as well as a control structure that determines how this knowledge is used. Declarative knowledge may include a property of a device model, such as the conductivity of a resistor, or a battery as a source of voltage. Procedural knowledge might be the method used to determine the distribution of voltages within a circuit. Control knowledge could include knowing that when one device's conductivity changes, the states of all other devices in the circuit change.

Various mental models can be specified for a domain, each of which represents a different conceptualization of domain phenomena. Within a causal model, a student can predict the behavior of a circuit knowing that a decrease in its resistance causes a decrease in voltage across the component. Within a functional model, she can explain the purpose of a circuit as a whole or as the sum of its components. The mental models can vary in their order of description: A zero-order model can reason about binary states of devices, such as "is the light on or off?"; a first-order model can reason on the basis of changes, "is the light getting brighter?"; a second-order model can reason about the rate at which a variable is changing. Moreover, models vary in their degree of elaboration or in the number of rules and constraints taken into account. The objective of learning is to achieve a coordinated set of expert-like mental models, that is, a set of complementary models for the same phenomena, behavioral as well as functional, qualitative as well as quantitative. Each type can be expanded and elaborated.

THEORETICAL BACKGROUND

Learning is viewed as a process of model transformation, as a progression through increasingly sophisticated mental models, each more adequate for a larger set of problems. Transformations entail changes in knowledge and structure. Changes in knowledge may involve adding qualifiers to rules, deleting rules, or adding new rules. Such changes, in turn, may result in restructuring existing knowledge. For example, a new rule learned in the context of a certain device (e.g., a battery) may be encoded as general rather than specific to that device. In this case, all other device models (e.g., switches, resistors, bulbs, transistors) inherit this rule. Model transformations occur in the context of solving problems, in response to demands of more complex problems that cannot be solved with the existing model. Facing an impasse, the student learns from examples and from explanations compatible with the next higher model. The new level of understanding is strengthened by success in solving problems.

The major emphasis in White and Frederiksen's work is qualitative models that support causal explanations. They argue that students should be initially exposed to qualitative causal reasoning about a domain that connects with their naive intuitive models of physical phenomena. The qualitative models enable students to build upon their naive but accurate intuitions and to override their inaccurate conceptions. The reasoning in their models is compatible with the general intuition that changes in states have precipitating causes. Because causality is directional (cause=>effect), the qualitative causal models are consistent with the view that the voltage applied to a component, for example, determines the current through that component. In contrast, if the student is presented only with quantitative expressions, causal relations between current, voltage, and resistance are obscure. Using the algebraic constraints for reasoning precludes a consistent mental model. Accordingly, they advocate that quantitative models of reasoning should be introduced only after the acquisition of a qualitative conception of the domain and should be taught as a logical extension of them.

INSTRUCTIONAL PRINCIPLES

White and Frederiksen have developed, so far, a progression of zero-order qualitative models for troubleshooting. The learning environment enables students to solve problems and to receive explanations and perform experiments while interacting with successive qualitative models. Each model is used to simulate the domain phenomena, to generate articulated explanations, and to provide appropriate problems.

Sequence and choice of models and problems The models become increasingly complex, yet are constructed to be compatible; early models are designed to enable later transformations with minimum reconsideration. Model choices are guided also by the ease of explanation for a current level of problem solving, although some of the acquired rules will have to be deleted in later more complex models. Problems are indexed according to models. Particular care is required in choosing the problems that trigger a change of model. In general, these problems should be just beyond the student's level of competence. They must be prototypical to make the model difference clear and should have no distracting causes. (Where this is impossible, extreme cases are used.)

Causal explanation Causal explanations are provided for each qualitative model. The system can turn any problem into an example and display the reasoning involved while it solves the problem. Also, at any stage during problem solving, the student can call for explanation either about circuit operation or about the logic of troubleshooting. To assure that the task is not too complex, explanations are pruned not to repeat what is known and to refer only to the information necessary at a given model level.

Teaching and supporting multiple learning strategies The system supports various learning strategies. Students can engage in open-ended explorations and request explanations, they can start by solving problems on their own, or they can request tutorial demonstrations. Within the linear curriculum for troubleshooting, students are free to decide whether, for example, they want to acquire a new concept or to differentiate between two concepts. The authors suggest, on the basis of preliminary findings, that students should be taught explicitly to apply the alternative learning strategies.

Minimization of error White and Frederiksen attempt to minimize error. They assume that, with careful presentations of models and problems and of feedback and explanation, in principle, errorless transition to the desired knowledge state is possible. The system, thus, does not deal with detection of bugs and misconceptions.

As criteria for learning, the authors suggest qualitative components of understanding such as order and level of elaboration of a particular model as well as the integration and coordination of behavioral, functional, and causal models. However, the qualitative measures of understanding are not implemented in the system. It is assumed that the student's understanding is compatible with the latest level of the model mastered within a tutoring period.

OVERVIEW AND ANALYSIS

The mental models that the program attempts to teach are not simply incomplete versions of expert models; rather, they are specifically designed for transition. Construction of models takes into account the initial understanding of the learner (e.g., that beginning students do not have a concept of a circuit or that they do not distinguish between a resistive and a nonresistive path) based on preliminary interviews and on observing students' progress when using the system. Also, although each model is designed to be modifiable to enable progressive upgrading and, ideally, should be compatible with a higher level version, considerations of learnability often demand the introduction of assumptions or rules lacking in expert models, which are later deleted or subsumed. The progression of models is an hypothesis about optimal transitions towards expertise based on articulation of the transition process itself.

The transition to expertise in the mental models' approach differs from that of knowledge engineering. GUIDON 2 provides the learner with an environment that enables exploration of fully developed expertise, albeit in decompiled form. The learner controls his or her own progress, and there is no predetermined and carefully designed transition path. The mental models' mastery model of instruction, by contrast, entails a strict curriculum, based on an hypothesis about the best transition route. The units of learning are not component productions, but bigger encompassing conceptual units.

In the current sequence of mental models, all models involve qualitative causal reasoning, although the designers acknowledge that explicating causality is insufficient for deep understanding. Thus, important questions are at what point in instruction other conceptualizations (e.g., quantitative and physical) should be introduced, whether these should be initially taught in a separate sequence, and how they should be integrated. Gentner and colleagues (e.g., Collins & Gentner 1987, Forbus & Gentner 1986) have suggested the importance of an analogical mapping process for integrating different models of a domain. Collins, Salter and Tenney (unpublished manuscript) have indicated, as well, that integration requires monitoring and checking for consistency, comparing the outcome of one line of reasoning to another. They also suggest that consistency checking should be based on central ideas that crosscut the various models.

Finally, it is of interest to note that, although the White and Fredericksen program addresses the issue of the initial state of the learner through preliminary studies of domain relevant pre- and misconceptions, the instruction does not accommodate individual differences on a principled basis. Further, the transition is grounded in a rational analysis rather than on tracing conceptual change or on a theory of such change. Such theories have recently become of major concern for many researchers (e.g., diSessa, unpublished manuscript, Chi 1988, Forbus & Gentner 1986).

COMMENTARY: AN AGENDA FOR THE FUTURE

We have described a set of instructional programs that teach different categories of human performance, deal with different subject matters, and derive from different traditions. At first blush, there is no general view of learning processes or of instructional methods. As gains are made in empirical and theoretical research on learning, one may wonder to what extent such differentiation will be necessary. Is the emphasis on automatic learning mechanisms best suited for acquiring efficient procedural skill, whereas conscious mechanisms, such as monitoring understanding or generating an explanation, must be emphasized for acquiring an organized body of knowledge? Does the choice to focus on learning of specific procedures require individualized instruction where errors can be minimized, whereas a focus on metaconceptual skills prescribes learning within a supportive social context that can encourage error detection? Should we allow, for the time being, that each category of performance warrants a different learning and instructional theory? That conclusion would echo Melton's sense, in 1964, of the conundrum.

> When one is confronted with a decision to use massed or distributed practice, to insist on information feedback or not to insist on it, to arrange training so as to maximize or minimize requirements for contiguous stimulus differentiation, etc., and discovers that the guidance received from experimental research and theory is different for rote learning, for skill learning, and for problem solving, taxonomic issues become critical and taxonomic ambiguities become frustrating, to say the least (p. 327).

Even if we accept that it will be difficult to achieve a unified theory of learning, we should attempt to discover grounds for integration of the key aspects of human competence in instruction. The apparent fragmentation may be due to each program's attending to one specific aspect of domain competence and neglecting and/or de-emphasizing others. The central concern with proceduralization of declarative knowledge in the CMU group's work allows only minimal attention to the structuring of knowledge and does not deal with processes of self-monitoring. The programs on cooperative learning, medical diagnosis, and knowledge restructuring do not attend to issues of efficiency and of automaticity. The mental models' approach does not deal with metacognitive skills, nor do the programs for reading comprehension strategies and heuristics for solving mathematics problems tackle the issue of knowledge structure. It appears to be as yet impossible in research on instruction to attend to the many ingredients of performance. Each of the investigators simplifies objectives by focusing on one aspect or another, choosing the aspect that seems appropriate to the domain and to the values, tradition, and techniques with which he or she is most familiar. It is good science to avoid confounded effects, but the eventual objective in these studies is obviously not isolated phenomena; competence is characterized by both efficiency and principled understanding, by both pattern recognition and conscious monitoring. Accordingly, the process of transition or the various learning mechanisms may not operate in isolation.

As the field of instructional psychology builds from the kinds of research examined here, assessing the potentialities for integrative approaches should be a recurrent theme. To design experimental programs aimed to foster integrated competences, it may be necessary to proceed by teaching relatively separate, yet complementary, components of performance in sequential, spiral, or alternating phases. Under some circumstances, a program might teach a skill to a high degree of efficiency, and then use it in the course of developing higher levels of cognitive processing in that domain. In this way, planning processes, inference, and changes in knowledge structures could take place with memory freed of the demands of an inefficient skill. In other situations, structures of conceptual knowledge and mental models could initially be taught or made available and practice with complex procedures would follow.

The danger of fragmentation in research is that an isolated focus on certain aspects of performance may explain the frequent findings that students can solve problems but have little ability to explain the underlying principles and that those who can recite or even explain the principles are sometimes unable to recognize the conditions of applicability or to manage the requisite procedures efficiently. A major instructional research task is to design programs that test approaches to the integration of competent performance, and perhaps the most successful approach will be able to test a mix of instructional principles. Evidence, for example, from developmental work (Case & Sandieson 1988a, b) shows that the ability to establish an appropriate conceptual representation constrains acquisition of strategies and procedures, but, at the same time, the degree of procedural efficiency constrains the complexity of children's representations. In other relevant research, training studies show that procedural skill is effectively acquired in the context of a supporting mental model (Kieras & Bovair 1984; Gott 1988). Perhaps, programs aimed at structuring knowledge could be expanded to include the practice required for the acquisition of a procedural skill. Attempts at integration promise to provide new grounds for the development of a more general theory of learning. Such a theory may include subprocesses such as those suggested by the current programs (e.g., knowledge compilation, failure-driven learning) or some new mechanisms that may operate in an integrated setting).

With respect to instruction, there are already certain major principles that are shared in the studies discussed, regardless of the aspect of competence or domain on which they focus. All programs advocate learning in the context of working on specific problems--be they those of writing code in LISP, understanding text, diagnosing a medical case, or describing an electric circuit. Thus, all investigators agree that useful knowledge is not acquired as a set of general propositions, but by active application during problem solving in the context of specific goals. Moreover, all programs recommend explication and modeling of the appropriate problem-solving structure and of the procedures or strategies entailed. The investigators also share the view that learning, in the sense of strengthening existing knowledge, results eventually from practice that minimizes error, and, except for the automatic process of knowledge compilation, they agree that failure or conflict trigger new learning. Moreover, categories of performance and related instructional subtheories may not necessitate different conditions for instruction. Instructional decisions about control, feedback, or about the structuring of the curriculum crosscut approaches. Such principles do seem a basis for studies that promise to inform a more unified theory.

In the programs reviewed, there seem to be two general stances toward instruction. In the mastery approach, the instructor is responsible for a specific transition path, building a curriculum that carefully fosters a progressive sequence of skills through appropriate tasks. This approach, which resembles behavioral programmed instruction or computer assisted instruction, is characterized by sequenced subgoals of partial or decomposed components of the total target performance. The mastery approach has been adopted for the acquisition of a proceduralized skill, for fostering conceptual evolution with mental models, and for teaching heuristics for mathematical problem solving. The second approach does not structure transition, but, rather, provides a learning environment that can assist the learner in coping with a complete and mature task. The learner is given certain tools or strategies to apply on his or her own, and where he or she is unable to do so, the tutor, the teacher, or the group provides assistance. Typically, a mastery model implies relatively close control, whereas a less structured curriculum gives the learner more responsibility. Among the approaches, however, there are variations in the amounts of control and freedom. The programs using knowledge compilation, coming from learning theory, exercise more control than the program for teaching heuristics for mathematics. Programs for shared learning, coming from a developmental-social tradition, appear to recommend more control and supervision than those coming from knowledge engineering.

This dichotomy may depend, to some extent, on the amount of inherent hierarchical structure or subskill interdependency in subject matters. Cognitive skills, metaconceptual strategies, and procedures for problem solving have different properties as a function of the knowledge domain. Procedural skills that are knowledge lean, those that can be practiced with a minimal or easily acquired knowledge base, might be learned in *one* way; cognitive skills that entail the constraints offered by an available knowledge schema, those that require inference from knowledge, hypothesis formation, and strategy selection based on emerging information, might be learned in another way.

From another perspective, the dichotomy is a function of research traditions and values. Those who study learning and instruction come to place different values on efficiency, command of factual information, reasoning ability, monitoring skills, and so forth. Designers of instruction may hold that thoughtful problem solving has greater utility than the acquisition of efficient procedural skill, or that procedural skill should precede the development of higher order processes, or that understanding and appropriate mental models are essential supports for the development of procedural efficiency. In current research, such general assumptions seem to be continuous with a researcher's training, the findings of older learning theories (e.g., Fitts 1962, Vygotsky 1978), cultural beliefs about learning, and commonsense observations of teaching and tutoring. But continued experimental study of phenomena of performance and instructional interventions will provide new information for learning theory. Using available and new tools for detailed description of ongoing cognitive processes, we need to study the phenomena of learning directly, within natural settings as well as within carefully designed instructional settings. Such studies will shed further light on issues raised by the work reviewed here. Research can now be shaped to examine the interplay between conscious mechanisms of inference and the automatic process of knowledge compilation, to explicate the mechanisms of internalization and the conditions that encourage it, and to delineate how failure-driven explanation fosters understanding and how conceptual models evolve and are integrated.

Another basic question is how initial knowledge is acquired. Anderson's and Clancey's programs, for example, assume that a certain amount of declarative knowledge has already been acquired through reading and listening when their instructional procedures are introduced. Such analysis is proceeding in research on reading and text comprehension (Kintsch 1988a, b, Just & Carpenter 1987). In addition, general learning abilities and knowledge-free problem-solving skills need to be further explicated (cf.

Nickerson et al 1985, Resnick 1987a, Sternberg 1986), particularly individual differences in how they are acquired and guide learning. To some extent, the mental models' approach addresses the introduction of initial structures on which learning can proceed, and programs on cooperative learning address the development of general skills for problem solving and understanding. However, in the main, differences between individuals are left unattended in the programs that have been discussed, differences that are inherent in misconceptions of knowledge in a domain and in the intuitions, theories, principled beliefs, and aptitudes that children and adults bring to subject-matter learning. The accommodation of the array of pertinent findings on the initial competence of the learner (cf. Gelman & Brown 1986) will be a significant watershed in attempts to build powerful accounts of learning.[2]

To conclude, it is apparent that the single most important contribution to date of the knowledge and methodology of cognitive science to instructional psychology has been the analysis of complex human performance. The design of instruction in the studies we have reviewed relies more on models of competent performances in specified areas of knowledge and skill than on models of how this performance is acquired. Anderson's work is the most rigorous in explicitly attempting to use instruction to test a theory of learning. But, in general, assumptions about learning, not well-specified theory, are loosely connected to instructional principles. Indeed, the technology of cognitive task analysis that has emerged is a crucial first step. Over 25 years ago, a major figure in training research offered that "perhaps the most important single contribution to the

[2]Other research areas that should be considered in the development of learning and instructional theory include current work on the analysis of classroom teacher performance (Leinhardt & Greeno 1986); learning in natural settings (Lave 1977, Lave et al 1984, Schliemann & Acioly 1988, Resnick 1987b); the technology of instructional design (Gagne 1987, Reigeluth 1983); machine learning investigations of explanation, discovery, and learning from examples (Michalski et al 1983, 1986); technical training in industrial and military settings (Halff et al 1986, Gott 1988, Lesgold et al 1988); and much work on artificial intelligence and tutoring systems (Wenger 1987).

development of training through research has been the determination of methods for the formulation of objectives of instruction" (Crawford 1962, p. 326). There have since been major improvements in both method and content; the theory underlying task analysis and our understanding of the nature of human competence has been greatly advanced. These advances constitute impressive payoff on the scientific bet, which we quoted earlier from Newell and Simon about cognitive science's emphasis, in its youth on performance. "Both learning and development must [now] be incorporated in integral ways in the more complete and successful theory."

An evolution of instructional theory and the learning theory that underlies it will come about by investigation of questions that emerge from work of the kind we have described here. Progress in an area is often made on the basis of instrumentation that facilitates scientific work, and, at the present time, a significant tool is the design of instructional interventions *that operationalize theory* in the form of environments, techniques, materials, and equipment that can be carefully studied. These investigations can be testing grounds for new theories of learning and instruction that will benefit both the practice of education and the advance of science.

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