Problem Solving in Medicine and Beyond: Transitions from the Naive to the Neophyte to the Master Clinician

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The naive learner's knowledge may be characterized in terms of rules and higher-order rules that are not in themselves adequate for solving desired problems, but which by proper combination can be made so. The neophyte's knowledge is likened to knowing explicit rules for solving particular problems. The master's, by way of contrast, corresponds to knowing rules consisting of more efficient procedures which operate on relatively complex structures. Processes of transition from naive to neophyte and from neophyte to master are shown to be explicable in terms of interactions among appropriate higher and lower-order rules governed by a single universal control mechanism. Incidental comparisons are made to other cognitive theories.

Why is it that some people can solve problems that others cannot? And, how is it that initially naive learners acquire new competencies—and gradually come to acquire the sort of mastery we normally associate with the expert? These are problems with which the first author has been concerned for many years, although little of this work has been done in medical areas. Recent work at Michigan State (Elstein, Shulman and Sprafka, 1978) and at McMaster (Barrows, Feightner, Neufeld and Norman, 1978) has only started to shed light on these issues. We believe, nonetheless, that the basic understandings we have achieved are equally applicable in medicine as in other areas. In this paper we shall briefly review some of the basic ideas and show how and why they apply in all areas.

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To see what is involved, let us first consider the game of chess. Specifically, consider the problem first from the standpoint of the naive learner, then from the standpoint of the neophyte—one who has already learned the rules of the game and can play passably by analyzing his moves very carefully and acting accordingly. Finally, we consider the chess master.

Depending on one's age, education, and experience, the naive learner enters into the experience with varying degrees of generalized knowledge which allow him to understand spoken or written directions, generalized strategies and techniques that might carry over from analogous games like checkers that the learner already knows how to play, including even some informal awareness of chess itself. On facing the task of learning to play chess, the learner must rely exclusively on the general learning capabilities, strategies and perhaps the general knowledge of board games which he already has. The newcomer must first learn the permissible moves for each of the possible pieces, how to anticipate an opponent's moves, and some generalized chess-specific strategies for beginning games and ultimately for producing checkmates.

The neophyte, by way of contrast, has acquired most of these skills, and with effort can play a passable game by carefully and systematically analyzing his moves. One characteristic of play at this stage is the relatively long period of time between moves required to "check into all possibilities", each of which may be analyzed to a depth of two or three moves in advance. The neophyte may also be able to use and detect subtle two or three move combinations.

To be sure, the chess master may also take considerable time before deciding on his next move, especially when playing with other chess masters. Even here, however, the chess master seems able to discard most moves almost automatically, concentrating on and exploring in detail only those few possibilities that make sense (see deGroot, 1956). This automatic, nearly instantaneous assessment of chess positions and possibilities becomes readily apparent in games the master plays with the neophyte. While the serious neophyte might spend minutes, even tens of minutes, analyzing a given move, the chess master might be seen to react almost instantaneously, often producing a checkmate within the first few moves. A chess master also remembers, has categorized, and can play from memory many hundreds or thousands of specific chess games.

We would propose that each of these stages is directly reflected in the learning associated with almost any area. Think for a moment about the field of medicine. On entering medical school, the typical student, talented though he may be, has little understanding of the intricacies of modern medicine. Again, he must rely primarily on the generalized information
gathering and problem solving skills one normally acquires during one's undergraduate years, together with premedical and related studies. Perhaps in a negative sense as much as a positive one, he also relies on his layman's understanding of how medicine operates. This knowledge and related skills and abilities provide the bases upon which the naive student must rely in acquiring medical knowledge.

Turning to the neophyte, there clearly are a wide range of students, including interns and residents, who might properly be placed in this category. In varying degrees, each can be seen to operate in a fashion quite analogous to that of the neophyte in chess. The neophyte student knows basic disease processes and the diagnostic process, and applies the systematic patient history-gathering techniques as they were learned during medical training. In diagnosis, he may explore each of the textbook possibilities one-by-one, gradually, with varying degrees of skill and certainty, narrowing down the number of possibilities—and all too frequently exploring unproductive possibilities by attending to apparently relevant but misleading cues or symptoms.

By way of contrast, the master clinician frequently sizes up situations almost immediately—acting on the basis of the overall context, including the physical appearance of the patient and his mannerisms, as well as specific symptoms and/or formal history. Tacitly, the master clinician can quickly eliminate many possibilities as highly unlikely, typically leaving only a few likely causes to be explored in more detail.

What is involved in these situations? We would propose that what has been described in the cases of chess and medicine is not really unlike what happens in almost any other area where one must learn how to solve problems.

Indeed, a number of theories have been proposed to explain how people solve problems (e.g., Chase and Simon, 1973; Kleinmuntz, 1956; Newell and Simon, 1972; Polya, 1962; Wertheimer, 1945). As is the case with all theories, they differ in comprehensiveness, cohesiveness, precision, parsimony and in the extent to which they are operational. Not surprisingly, we believe that structural learning theories (e.g., Scandura, 1971, 1973, 1977, 1980) best fulfill these various requirements. In structural learning theories it is assumed that what a person does in a given problem-solving situation depends on two things: (1) knowledge the person has and (2) certain general capacities which apply universally in all problem solving tasks.

Two kinds of knowledge fall in the category of prior or available knowledge: (A) knowledge of procedures or algorithms and (B) knowledge of structures or propositions. Procedures or algorithms might be termed prescriptive knowledge in that they provide step-by-step prescriptions for
telling the student exactly what to do and when to do it. The subtraction algorithm of ordinary arithmetic is one such procedure or algorithm. Don't be misled into thinking, however, that algorithmic knowledge is restricted to such things as subtracting numbers. Algorithms exist for solving any number of other kinds of tasks as well. Indeed, as we shall see, algorithms play an important role in all problem solving. Though space is not available to go into this here, algorithms have been developed for proving complex theorems in mathematics (Scandura, 1977), for constructing complex geometric figures using straightedge and compass (Scandura, Durnin and Wulfeck, 1974), for solving Piagetian tasks in testing young children to determine their developmental stages (Scandura and Scandura, 1980), and so forth (see Scandura, 1977, 1978, 1980).

Unlike procedures, structures represent the static aspects of knowledge. Structures are more holistic. For example, the knowledge that the chess master might bring to bear to rapidly assess particular board configurations is more naturally represented in terms of structures.

The basic theoretical construct in structural learning theories is that of the rule (e.g., Scandura, 1970). Rules may be characterized as triples, consisting of a domain, or class of structures to which the rule applies, a range, or set of anticipated results of applying the rule, and a restricted type of procedure or algorithm which operates on the structures in the domain (and generates structures in the range).

In effect, the rule is a theoretical construct that includes both procedural and structural knowledge. The domain of a rule constitutes a class of structures or a structural type and is much like what other theorists have called a "frame" (e.g., Minsky, 1975). As we shall see later, the rule is a very flexible construct and allows one to characterize the knowledge available both to the neophyte and to the master.

In the first author's research, it has been found that problem-solving behavior can be explained in a surprisingly simple way: Thus, in addition to learner-specific knowledge, it appears sufficient to assume only two problem-solving universals, a control mechanism and processing capacity.

The control mechanism, in concert with specific problems, provides a means of determining which of a person's available rules to use and when to use them. Roughly speaking, the control mechanism operates in the following manner: When confronted with a problem, the problem solver first checks each rule in his processor to see if the given of the problem is in the domain of the rule and that the range of the rule contains the problem goal. If exactly one rule satisfies these conditions, it is applied. If not, the problem solver checks the range of each rule to see if it contains a rule \( r' \) such that the problem given is in the domain of \( r' \) and that the range of \( r' \) contains the problem goal. If exactly one higher-order rule
satisfies these conditions, it is applied—thereby generating a solution rule that does satisfy the original problem conditions.

In general, when no solution rules are immediately applicable, or when there is more than one, the search moves to the next higher level to check for higher-order rules which have the potential to generate a rule that applies. Once a rule has been selected and applied, the output of such application (possibly a newly generated rule) is added to the set of available rules. Control then reverts to the next lower level where the search continues, this time to a rule set that contains the new rule.

Although it would take use too far afield to go into details here, the restrictions placed on the procedures of rules correspond precisely to the hypothesized control mechanism. Specifically, rule procedures are not allowed to generate new subprocedures and later "call" (use) them. Where needed to explain (or predict) behavior, the control mechanism takes over this "calling" function. The control mechanism effectively eliminates the need for "recursion" in procedures (of individual rules) while retaining the power and efficiency it provides.

Since both rules and the control mechanism are theoretical constructs one might wonder why they have been separated (especially since the distinction is arbitrary from a formal/mathematical point of view). The main reason one must distinguish them in instructionally-relevant theories is because some constructs (i.e., lower and higher-order rules) may have to be learned whereas our research shows that others never do. Specifically, this research shows that the hypothesized control mechanism is uniformly available to all school-age learners.

In the first (Scandura 1971, 1974) of a long series of experiments (e.g., Scandura 1973, 1977) 24 young children were trained on simple rules of the form \( A \rightarrow B \) and composite rules of the form \( A \rightarrow B \rightarrow C \) (where \( A, B, C \), etc. were objects to be traded like paper clips, pencils, erasers, etc.). Half of the children also were trained on a higher-order rule, which if applied to pairs of rules of the form \( A \rightarrow B, B \rightarrow C \), generated corresponding composite rules of the form \( A \rightarrow B \rightarrow C \).

Then, all of the children were trained on new \( A' \rightarrow B', B' \rightarrow C' \) rules which they had never seen before. The children who had been trained on the higher-order, as well as the new rules, ALL succeeded on the crucial \( A' \rightarrow ?C \) test problem. Those who were not trained on the higher-order rule uniformly failed.

These results and many others like them indicate two things:

(a) Even young children come "wired in" with something equivalent to the postulated goal-switching control mechanism. If, for example, the \( A' \rightarrow B', B' \rightarrow C' \) and higher-order rules had been programmed into a "computer and then it was presented with the problem (\( A' \rightarrow ?C' \)) of trading
C' objects for A' objects—nothing would happen!! The computer would not know what to do with the information unless it had been pre-
equipped with an adequate control mechanism.

By way of contrast, having failed to find a solution rule available, the higher-order rules children apparently searched for and found an available higher-order rule appropriate to the situation. They applied it and generated a needed A'→B'→C' rule. Control then returned to the original level and the search yielded this newly derived rule. Subsequent application solved the A—?C' problem.

(b) The fact that the non-higher-order rules children failed indicates that people are not necessarily able to compose (put together) arbitrary pairs of rules of the form A→B, B→C. Consequently, assuming a control mechanism that allows for arbitrary composition of rules, as is common in many cognitive theories, is TOO strong an assumption. Such a mechanism would not be universally available to all people and, hence, would be of limited value in explaining human cognition.

Processing capacity is the second hypothesized cognitive universal (Scandura, 1971a, 1973; Voorhies and Scandura, 1977). In structural learning as in most cognitive theories, learners are assumed able to process a fixed number of entities (or "chunks") at any one time. In contrast to most cognitive theories, however, working memory in structural learning theories is assumed to hold not only data, the stuff on which rules operate, but rules (processes) themselves (e.g., Scandura, 1971, 1973). In more recent years, other theorists appear to be moving in a similar direction (e.g., Anderson, 1976; Case, 1978).

This difference has a number of important implications pertaining to a variety of memory phenomena, only some of which have been investigated empirically. Unfortunately, most of the implications are rather subtle and going into them here would detract from our main purposes. The interested reader is referred to Scandura (1973, Chapter 10) and Scandura and Brainerd (1978, pp. 155–166) for further discussion.

To see what is meant by processing capacity, imagine the following task. If a list of numbers were to be read to you and you were asked to repeat them back, the list 2, 4, 5 would present no problems. Yet on a first attempt, the list 7, 3, 9, 1, 5, 7, 4, 6, 8, 5, 7, 9, 5 would probably be impossible to repeat. What is the difference? Clearly, one can only keep so many things in mind at one time.

Suppose, however, that you were to practice these numbers over and over. You could certainly memorize the digits so that they could be repeated on cue. Once this has been accomplished, it is no longer necessary to remember all of the individual digits as digits. In order to think about a previously memorized list, you would need only remember
what list it was, perhaps by assigning it some label to distinguish it from other lists. And, anytime you wanted a particular digit in that list, you would FIRST call on that list as a unit, as an integrated structure or what Miller (1956) called a “chunk.”

The above discussion has important implications for problem solving. In particular, having already learned a rule (so that it is available) does not necessarily guarantee that the rule may be carried out effectively or efficiently. For example, the rule may impose a heavy load on the user’s processor, thereby requiring the student to resort to pencil and paper or other memory aids. Hence, once a new rule has been learned, the emphasis changes from ACQUISITION to LEVEL OF SKILL. In structural learning theories this means acquiring more efficient rules.

The question is, “How does the learner learn these more and more efficient rules”? Oddly enough, in structural learning theories this process of AUTOMATIZATION takes place exactly as in all other learning. In particular, the learner either uses higher-order rules to eliminate unnecessary or redundant steps, in the process generating more comprehensive rule domains (containing “chunks” or structures capable of holding increasing amounts of data), and/or he learns new, more efficient rules for dealing with particular problem subtypes (e.g., Scandura, 1973, p. 104).

For example, in the case of ordinary addition, most people eventually learn short cuts such as those for adding numbers that end in zero or five. Over time, we also memorize special facts, such as $75 \pm 50 = 125$. Higher-order automatization rules have the effect of incorporating these special facts into new, more efficient short-cut rules for performing more complex additions.

In these cases what tends to happen is that the procedures associated with rules tend to become simpler and/or more efficient. The structures on which the rules operate correspondingly become more comprehensive. For example, in chess, sequences of play, each step of which is viewed distinctly by the neophyte, gradually come for the chess master to be viewed as holistic structures. For the master clinician, the individual consideration of diseases that might explain a set of symptoms becomes an automatic, subconscious selection and elimination process.

At the risk of oversimplification, the neophyte’s knowledge can be likened to remembering each of the individual digits separately, or knowing inefficient rules. The master’s, by way of contrast, corresponds to remembering the list as a list, bringing the individual digits to mind only as needed, or knowing procedurally more efficient rules with more highly structured domains. The neophyte physician in training tends to remember individually each of the diseases that may be causative of each
symptom; the master has learned to group these symptoms and diseases as unitary clumps, which allow him to rapidly sort out the complicated cases with which he might be confronted.

To summarize, the naive learner's knowledge consists of rules and higher order rules that are not in themselves adequate for solving desired problems, but which by proper combination can be made so. The neophyte's knowledge can be likened to knowing explicit rules for solving particular problems. The master's, by the way of contrast, corresponds to knowing more efficient rules—which operate on more complex structures.

In order to avoid any misunderstandings, let us emphasize that what has been done so far is to merely sketch some of the major ideas involved in understanding and explaining how people solve problems. It is intended primarily as a basis for the second part of this paper. The medical educator needs to know how one might facilitate the learner's mastery of problem-solving skills; specifically, how one can facilitate transfer from the naive medical student to the neophyte physician in training to the master clinician.

A PROTOTYPIC INSTRUCTIONAL STRATEGY BASED ON A STRUCTURAL LEARNING THEORY

Instructional implications of structural learning theories are perhaps best seen by example. Let us first consider column subtraction problems as a very simple prototype, and then look at a simple medical example.

In order to utilize structural learning principles in designing instruction, the ESSENTIAL first step is to identify: (1) the educational goals—what the learner is to be able to do after instruction and (2) prototypic cognitive processes or rules—what the learner must learn if he is to successfully perform tasks associated with the educational goals.

In the case of subtraction, for example, let us assume given a column subtraction problem that our educational goal is to find the difference. By a prototypic rule, or cognitive process in this case, we refer essentially to what the learner must master in order to subtract numbers.

"The Structural Learning Theory" provides a general method of analysis, called Structural Analysis, by which the rules to be learned can be derived from suitably operationalized educational goals. While there are many details still to be completely objectified, the method is relatively systematic and has been applied successfully in analyzing a wide variety of content.

The first step in structural analysis involves selecting a representative sample of problems associated with the goal in question. Representative problems may be defined as problems that the "teacher" feels best
represent how a knowledgeable person should solve the problems. In the case of simple subtraction, this might include problems like:

\[
\begin{array}{ccccc}
9 & 879 & 432 & 402 \\
-5 & -325 & -129 & -129 \\
? & ???? & ??? & ??? \\
\end{array}
\]

The second step in structural analysis involves identifying rules which make it possible to solve each of the selected problems. Identifying such rules involves several identifiable substeps:

(a) Assumptions must be made regarding the MINIMAL ENCODING AND DECODING CAPABILITIES of the students in the target population. In the case of second graders, for example, the teacher/analyst would normally assume that all students are able to distinguish "the minus sign", the individual digits 0, 1, ..., 9, the columns, the rows, and that all are able to write the individual digits in desired locations. The present illustration builds on this assumption. Consequently, the remainder of the analysis will be inadequate JUST to the extent that these assumptions are in error for students in any given target population.

(b) The analyst must decide the SCOPE OF EACH OF THE REPRESENTATIVE PROBLEMS. This scope effectively defines the domain of the rule associated with the prototype. The problem

\[
\begin{array}{c}
432 \\
-129 \\
\end{array}
\]

for example, might be held prototypic of the entire class of column subtraction problems, namely those formed by varying the individual digits 0, 1, ..., 9 and/or the number of columns. Indeed, in the present case, each of the selected representative problems is prototypic of this same domain. Consequently, in the present case it is reasonable to assume that there is only one domain, the domain of column subtraction problems.

(c) Next, the analyst must IDENTIFY THE STEPS (operations and decisions) INVOLVED IN SOLVING each of the representative problems. These operations and decisions must be sufficiently simple that using them refers only to abilities that are assumed available to ALL students in the target population (i.e., encoding/decoding capabilities). The operations also must be ATOMIC in the sense that, for each student in the target population, the ability to correctly use an operation once is indicative of uniform success and, conversely, for failure.

The flow diagram in Figure 1 depicts the procedural portion of a rule
based on equal additions. In this rule, it is implicitly assumed that each operation acts only on digits, rows and columns—consequently, the previously referred to need to assume certain minimal encoding/decoding abilities. The decisions of this procedure (e.g., Is top number greater than bottom number?) constitute additional assumptions concerning minimal cognitive ability. According to structural learning principles, only to the extent that these assumptions are met will this subtraction rule provide a useful and operationally precise basis for designing efficient and effective instructional strategies.

More could be said about the actual processes by which such rules are constructed but intensive work in this direction is currently underway and going more deeply into it here would detract from our main concerns. The essential thing to emphasize is that the use of structural learning theories for purposes of designing instruction necessarily begins with a rule-based analysis of the subject matter (broadly conceived) in question. While structural analysis is more general, in this sense it is quite analogous to traditional task analysis (Gagne, 1962). Notice, in particular, that nothing has been said about a taxonomy of subject matter content; ALL content from a structural learning perspective must be analyzed. Some types, of course, such as our subtraction example, are easier to analyze than others.

Once an ANALYSIS HAS BEEN COMPLETED, designing an EFFECTIVE INSTRUCTIONAL STRATEGY FOLLOWS DIRECTLY AND PRECISELY FROM THE THEORY. Specifically, once an analysis has been completed, one knows (a) what the student is to be able to do once he has achieved the educational objective (e.g., solve arbitrary column subtraction problems) and (b) what the student must learn in order to be able to do that (i.e., the equal additions rule).

Given this information, the FIRST THING one must do in designing an effective instructional strategy is to DETERMINE WHAT EACH STUDENT ALREADY KNOWS, specifically, that part of what the student knows which is directly relevant to what one wants the student to learn. The process by which this is accomplished has been detailed in the literature (e.g., Scandura, 1971a, 1973, 1977; Durnin and Scandura, 1973) and we will not consider it here. It is sufficient for present purposes to observe that solving particular subtraction problems involves following one and only one path through the subtraction rule. In effect, there is a unique class of problems associated with each path through the rule. (Note: There are a finite number of paths associated with any given rule.)

A basic principle in structural learning theories is that rules must be represented in terms of operations and decisions that are atomic; they are either totally available or unavailable to any given learner in the target population (i.e., the population the analyst had in mind in performing the
structural analysis). The existence of such a representation can always be guaranteed (e.g., Scandura, 1971a, 1973; Suppes, 1976).

In effect, success or failure on any one problem associated with a class of problems provides complete information as to the availability to the student of the corresponding path. For example, the problem

\[
\begin{align*}
879 & \quad -325 \\
\hline
\end{align*}
\]

is solved by following the path in Figure 1, defined by operation one, then two, then three, and back to two and three, then two and three again, before stopping.
By testing on a small, finite set of problems, it is possible to identify precisely and unambiguously which parts of the subtraction rule any given individual knows and which parts the student does not know. Such testing, in effect, defines the student's entering level. In this regard, more can be said about such things as testing in situations where meaning or more than one rule is involved and about increasing efficiency via sequential testing (e.g., Scandura, 1971, 1973, 1977) but this is not necessary for present purposes.

PRESCRIBING INSTRUCTION, then, follows directly from what the student knows. All one needs to do is to IDENTIFY THE MISSING PORTIONS OF THE DESIRED SUBTRACTION RULE AND TO PRESENT THEM TO THE STUDENT. The theory is neutral on whether this information should be presented, say, in an expository or a discovery manner. Thus, for example, deciding on the appropriate method of presentation depends on secondary objectives that the teacher may (or may not) have in mind (e.g., to help students learn how to detect regularities). The important part, insofar as being able to perform subtraction is concerned, is simply to be able to perform according to the rule.

As an illustration, suppose a student's knowledge may be represented by the flow diagram shown earlier, minus only the loop involving operation five (add 10 to top and subtract, go to next column and add 1 to the bottom). In this case, the instructor would need only to make sure that the student knows, at the appropriate points, how to add 10 to the top number in the column and how to add 1 to the bottom of the next column. Where the student knows less, of course, one would start with the simpler prototypes (partial rules representing what the student knows) and gradually "elaborate", or add increasing detail until the student has mastered the entire rule.

To summarize, we must emphasize that this illustration of prescriptive aspects of structural learning theories constitutes only a simple prototype. It "epitomizes" the instructional aspects of the theory. The theoretical system itself provides a far more generalized basis for instructional prescription—which, in principle, may be used with any subject matter (or educational goal) that might be of interest.

A Medical Example: An example in which structural analysis is applied to a problem in medical training might more fully illustrate how these concepts could be applied in medical education. Medical diagnosis is a highly interrelated and complex process, as indicated by the landmark studies by Elstein, Schulman and Sprafka (1978) and by Barrow, Feightner, Neufeld and Norman (1978).

To illustrate use of the analytic process, a segment of a diagnostic process has been selected for illustrative purposes. A general algorithm,
shown in figure 2, deals with the identification of the common cold and evaluation or search for complications or other diseases that may initially present in a manner similar to the common cold. Environmental, history and potential psychological factors are also briefly treated by this model.

The general educational goal is to be able to discriminate between the sign and symptom clusters that characterize different diseases, i.e., making a differential diagnosis. Clearly, this process requires a great deal of knowledge; for example only a small domain of that knowledge is sampled. However, this access to a small domain of knowledge characterizes the normal process that medical students use for learning to make differential diagnosis. They are exposed to repeated cases in which they pursue the process illustrated by the algorithm in figure 2.

The first step in this structural analysis involved selecting representative instances of (i.e., hypothetical patients with) the common cold, or common complications or diseases with similar initial presenting symptoms, as representative domain of the problem domain associated with the educational goal. This domain defines the class of diagnostic tasks, the identification of possible diseases that may present in a manner similar to common cold or be a complication of a common cold. This example was designed for the naive learner, thus, symptoms and problems that normally might not be consciously considered by a practicing physician were included. Likewise, some diseases that might be investigated by the sophisticated clinician under certain circumstances were not included.

The procedural portion of a possible rule for discriminating a common cold from other diseases that initially present in a similar way is shown in figures 2 and 3. Figure 2 depicts the entire algorithm, but for simplicity, several aspects of the rule are only implicit. For example, the phrase, "note presenting complaint" implies that the student hears a complaint from the patient and makes a written or mental note of it. Likewise, where the algorithm specifies that the student should check for something, it is implicit that the student asks questions of the patient that are specifically directed toward the symptoms in questions, or performs appropriate physical examination activities in order to test for symptoms in question, such as detection of infection in mucous membranes, or palpation of glands. For written simulations, of course, questions concerning the outcome of these physical examination activities could be asked of a data base. Reference is made to several lists of symptoms and factors in Tables I through IV. A more detailed illustration of the implied comparison process is given in figure 3, which is slightly abbreviated due to space limitations. The flow chart in figure 3 identifies the steps involved in solving the problems.

In effect, the example in figure 2 utilizes a shorthand for a large number
FIGURE 2 General Algorithm for common cold.
FIGURE 3 Specific steps in the algorithm presented in Figure 2.
FIGURE 3 (continued)
TABLE I
Symptom Group I, typical of the common cold.

I. Consider common cold if patient has the following symptoms.

1. Abrupt onset of symptoms
2. Scratchy throat

3. Sneezing
4. Rhinorrhea
5. Upper respiratory involvement

6. Malaise
7. Low grade fever (to 102°F) in children
8. Hacking cough

A

most of these occur simultaneously

B

9. Laryngitis—mild
10. Tracheitis—mild
11. Substernal tightness—mild

These may be present

TABLE II
Symptom Group II. typical of complications that may occur from the common cold

II. Look for complications that may be indicated by the following signs and symptoms:

A. Pain, tender, and or swollen sinuses—suspect sinusitis
B. Inflammation of adenoids—suspect adenoiditis
C. Inflamed eustachian passages—eustachitis
D. Throat pain and dysphagia—suspect acute laryngitis
E. Inflamed trachea—suspect tracheitis
F. Earache, possibly with fever, nausea, vomiting and diarrhea in young children—suspect acute otitis media
G. Sore throat with chilliness, back and muscle pain, increasing sputum—suspect acute bronchitis

TABLE III
Symptom Group III, typical of diseases that may initially present like a common cold.

III. The following signs and symptoms in addition to cold symptoms indicate more serious diseases:

A. High grade fever (>102°F)—possibility of Measles, Streptococcal pharyngitis, Meningitis (especially if unidentified origin), Influenza (especially epidemic), Rubella
B. Sore throat/Pharyngitis—possibility of acute laryngitis, acute bronchitis, measles, strep, meningitis, influenza
C. Headache—possibility of diphtheria (children), meningitis, influenza, rubella
D. Dysphagia—possibility of acute laryngitis, diphtheria, strep.
E. Anorexia—possibility of whooping cough, allergies
F. Pruritis, lacrimation—allergies
G. Vomiting—meningitis, whooping cough
TABLE IV
Groups IV and V that contain environmental and predispositional factors that should be considered.

IV. The following predispositional or environmental factors indicate consideration of other problems:

A. Season of year for allergy reactions—with allergy symptoms
B. Epidemics, high prevalence in population and for exposure—influenza, measles, diphtheria, rubella
C. History in patient—allergies, sinusitis
V. Sensitivity to potential psychological/attention-getting factors

of problems. For example, a comparison of the basic cluster of symptoms related to common cold with each of the complications in more serious diseases constitutes an individual problem. Thus, the algorithm could be written so that these individual comparisons could be made; figure 3 illustrates this to some extent. Consequently, these flow diagrams are applicable to a large number of problems, those characteristic of the domain of interest.

Several abilities are assumed available to the students who completed this example, namely, knowledge of the appropriate symptoms associated with each disease, an ability to remember what has already been learned about the patient, and an ability to remember the potential complications and other diseases that may follow from or be associated with the basic symptom clusters. Furthermore, it is expected that the student possesses adequate questioning skills and is able to make adequate discriminations where required, e.g., different degrees of malaise, the existence of clinically significant infection, etc. It is assumed that these operations are atomic, but given the complexity of this type of task, it may be difficult to verify that assumption.

The instructional strategy that may follow from this analysis might consist of several parts. Students could be asked to list the items in categories I, II and III (Tables I, II and III); they could be asked to list the environmental or predisposing factors in categories IV and V (Table IV). These would constitute crucial prerequisites.

For diagnostic purposes, assuming availability of the prerequisites, the entire system could be sampled by a number of simulations in which the student is asked to perform the diagnosis by asking questions of each simulation and handling the appropriate responses in an acceptable manner. Each simulation would contain different sets of symptoms sampled from the established domain. Errors in the performance of these
tasks would indicate specific deficiencies in the student's knowledge (of the solution algorithms) which could be rectified through further instruction.

This represents an initial attempt to utilize structural analysis to analyze a medical diagnostic situation. Clearly, additional refinements need to be made, and the development and testing of models of this nature will provide further information concerning the extent to which particular operations and steps can be considered truly atomic at various phases of medical training. Future work of this nature is planned.

Achieving Mastery: What has been described so far corresponds to aiding the learner in his passage from the naive to the neophyte. Unlike the naive learner, who enters the problem solving situation with only prerequisite skills and knowledge, the neophyte knows, at least in a textbook sense, how to deal with the problems at hand. In the present case, one who has learned the subtraction algorithm would know how to solve subtraction problems perfectly well. Indeed, in principle, given any subtraction problem, the neophyte could generate the appropriate difference.

One might wonder, therefore, whether learning stops here. A little further thought, however, will convince us that there are indeed differences among people who know how to subtract numbers. Thus, for example, whereas the neophyte goes through every step of the algorithm systematically and in detail, others introduce shortcuts of varying degrees of sophistication. It is unlikely, for example, to find an experienced financial analyst performing preliminary calculations in longhand. Indeed, in this regard, we are not simply referring to the availability of calculators, but to the skilled analyst's quick, insightful ESTIMATIONS that allow him to evaluate far more quickly than the neophyte the profitability of particular courses of action.

We would propose that as in chess, and other areas of complex problem-solving, these HOLISTIC SKILLS are acquired gradually as a result of introducing shortcuts into the problem-solving process. Thus, rather than applying the subtraction algorithm as such to the problem of subtracting 350 from 500, most adults would simply "know" that the answer is 150. With additional skill and practice, many people learn to consider such problems as wholes. In addition to developing effective shortcuts for solving the problems, they may even learn the exact differences attached to particular pairs of numbers (such as 500 and 350). Certainly, the problems that have been described in the case of arithmetic are not of the same order of complexity as those in medicine, or even in chess. We would propose, nonetheless, that they are of the same genre.

In medicine, the neophyte learner investigates each symptom and disease in turn, as illustrated above. However, with experience and exposure to
numerous instances of a particular disease, the neophyte starts to deal with clusters of symptoms as a whole rather than with each in turn. For instance, in the example above, the scratchy throat, sneezing, rhinorrhea and abrupt onset would be seen immediately as a whole which indicates a common cold. Other groupings of symptoms would be sought in the search for complications or more serious problems. This process would result in more rapid handling of the problem and is analogous to the shortcuts taken by solvers of mathematical problems of chess players who “see” specific combinations of moves on a particular section of the chess board.

Before showing more precisely how one might pass from the neophyte stage to that of the master, several points must be made.

(1) First, it is a mathematical fact that anything that can be represented as a procedure can also be represented as a cyclic structure. Consider, for example, the case of the young child learning to do arithmetic. The child may first learn to subtract by going to the first column, testing to see if the bottom number is larger than the top, and so on. For the neophyte, all of these steps are taken sequentially and systematically in order. It does not take long, of course, for the older child to learn to eliminate many of these steps. For example, many adults have learned how to subtract multidigit numbers directly, by-passing the originally taught algorithm entirely.

(2) Second, it is the PROCEDURE IN THE RULE THAT TAKES THE TIME. Following a procedure, cognitively or otherwise, involves taking a series of steps, each of which requires some finite time to carry out. The DOMAIN OF A RULE, by way of contrast, is TESTED HOLISTICALLY, all at once. Thus, for example, whereas the neophyte can tell almost immediately which problems are subtraction problems and which are not, it takes him some finite time to actually generate a SOLUTION to particular subtraction problems.

(3) Third, the reason the master typically takes less time in solving a problem is that all other things being equal, the rules of knowledge he uses involve relatively simple procedures. Much of the master’s knowledge is absorbed into relatively complex domains (of rules) which tell him when to apply this or that procedure. When a class of tasks has been “fully” mastered, the procedural part of the rule frequently amounts to little more than relating a given type of situation to the appropriate response—for example, where the master clinician assesses a complex set of symptoms and immediately proposes a diagnosis, or when the chess master quickly decides on his next play.

(4) Fourth, the time-tested way of passing from neophyte to master is that of practice. Clearly, by gaining experience and going over greater and
greater varieties of problem-solving situations, the neophyte gradually learns more and more efficient ways of dealing with those situations.

In structural learning theories, as we mentioned above, mastery is achieved in the same way as all other learning—by the application of higher order rules which generate new, more efficient rules.

To illustrate how learners achieve mastery, consider Figures 4 and 5.

![Flowchart diagram](image)

**FIGURE 4** One column addition algorithm.

The procedure of Figure 4 provides for addition one column at a time. For example, the sum of

\[
4322 \\
+ 2540 \\
\hline
\
\]

would be determined by the simple path consisting of going to the first column (operation 1), adding the digits 2 and 0 (operation 2), writing 2
below the line (operation 3), continuing to the tens column (operation 4), adding 2 and 4 (operation 2), and so on.

By way of contrast, the procedure of Figure 5 provides for adding two columns at a time. This is accomplished by operating on more complex substructures (i.e., pairs of columns) at each step. This time, the first two columns are added simultaneously, and then the third and fourth.

The two procedures are obviously very similar. While the individual steps are different (e.g., adding pairs of two digit numbers vs. pairs of one digit numbers), the overall "flow of control" is identical in each. Indeed, the main difference is that the structures associated with (the rule of) Figure 5 are more complex than those associated with Figure 4.

The relevant question here is how a person knowing the rule of Figure 4 might come to know the more efficient rule of Figure 5. Or, put differently, where do higher-order rules come in? In this case, in operating on the rule of Figure 4, the higher-order rule substitutes new operations
and decisions while maintaining the overall flow among corresponding components. For example, the basic addition facts of Figure 4 are replaced in Figure 5 by facts to $99 + 99$. Correspondingly, the structures on which these "facts" operate are changed from pairs of one-digit numbers to pairs of two-digit numbers. In effect, the number of algorithmic steps necessary to solve any given addition problem is reduced precisely because the eliminated steps have been absorbed into the more complex structures on which the procedure operates.

In presenting this example, we make no claims that master arithmeticians necessarily add by pairs of columns (although some undoubtedly use variants), nor do we claim that the way they learned such rules is the first place is via any one particular higher-order rule. The point is simply that they do learn some such rule and that they learn it by means of some higher-order rule.

Moreover, once learned, a higher-order substitution rule of the sort sketched could be used to learn more efficient variants of other computational rules. It takes little imagination, for example, to conceive of an equal additions (or more familiar borrowing) rule in subtraction that operates simultaneously on pairs of columns.

The work at Michigan State and McMaster has led to some basic understandings of the way master physicians solve problems, but their work has raised more questions than it has answered. As Barrow's et. al. (1978), point out, "...the practical questions of how to teach problem-solving remains unanswered". (p. 255) They recommend work on methods to improve the quality of hypothesis and a search for strategies to enhance storage and retrieval of hypothesis from memory. The methods described in this paper may constitute such strategies. However, only intensive research will be able to determine that for certain.

By way of conclusion, the question we leave you with is as follows: Is it necessary in training medical problem solving to rely primarily on experience and trial-and-error? What if we subjected medical diagnosis to a more intensive process of the kind illustrated above? Indeed, a number of algorithmic analyses of medical problem solving have already been developed and published in scientific journals (e.g., Patient Care Flow Charts). Suppose we were to utilize such algorithms and analyses more directly in our instruction. Initially, these algorithms might provide a systematic basis for passage from the naive to the neophyte stage.

But even after the underlying rules have been mastered, could not related analysis provide more precise prescriptions as to the kinds of hints and specific information (e.g., replace one column with two) that the neophyte might utilize in his passage from process to structure? Instead of relying solely on practice and experience, might not students be taught
higher-order rules which allow them to derive on their own more efficient versions of previously learned rules? In structural learning research, it has been found that this to be not only possible, but highly feasible. In studying problem solving (Scandura, 1977; Scandura and Scandura, 1980), for example, we have been able to systematically facilitate children's passage from one developmental stage to the next—from naive to neophyte, and from there to the master. Can these ideas, which are theoretically possible, be used successfully in the medical area? We would propose this as a question for your consideration.

In conclusion, we would like to call your attention to certain theoretical points which have been detailed in the literature (e.g., Scandura, 1977, 1980) elsewhere but which are only implicit in the above discussion. Notice first that individual knowledge is measured in relativistic terms. What the learner knows about subtraction is measured relative to what it is we want him eventually to learn, namely, the entire subtraction algorithm. (In the more naturalistic setting, as opposed to one involving education, what must be learned is replaced by a prototypic characterization of what the idealized learner knows. For example, in the case of logical thinking, one might characterize, as Piaget has done, the idealized knowledge available to children performing at various developmental levels.)

Second, measuring knowledge in relativistic terms makes it possible not only to operationalize individual knowledge, but to do so in a generalizable way. In particular, this approach avoids the dilemma faced by the normative experimental methods of traditional cognitive psychology (e.g., Scandura, 1971), on the one hand, and individualistic computer simulation methods (e.g., Newell and Simon, 1972), on the other. Thus, for example, normative data obtained in the traditional experimental paradigm refers to average behavior and may have little to do with how individuals perform on particular problems. Conversely, whereas simulation methods do deal with individual behavior, they do so in a nongeneralizable way. A different theory may be needed to model the behavior of each individual (e.g., see Scandura, 1977, 1980).

Third, we would like to reemphasize the paradigm Scandura introduced some years ago for studying complex human behavior (e.g., Scandura, 1964, 1970, 1971a). The first step in this research methodology involves structural analysis. Once the domain of interest has been established, the next step is to identify prototypic or idealized ways in which target populations of students may be expected to deal with that domain. Only after this step has been completed can one progress to the next step, that is, the assessment of individual knowledge (e.g., Scandura, 1971a, 1977). This assessment, then, plus the universals of cognitive behavior, provide the basis upon which we may predict and/or control student learning.
In effect, in structural learning theories, content, individual differences, and cognitive universals are all treated within a single, unitary system. Scandura has argued at length in this regard that not just any cognitive theory will serve instructional needs (e.g., 1980). Close interrelationships exist among the constructs and assumptions used to characterize what is to be learned, the learner's cognitive processes and the measurement of individual knowledge. These interrelationships place severe constraints on the form of any viable theory—a form that conforms to the class of content-specific structural learning theories. Indeed, there is strong reason to believe that any cognitive-based and operational instructional theory that deals with individual behavior in a generalizable way will necessarily be a structural learning theory (e.g., Scandura, 1980).

As Scandura has argued elsewhere (e.g., Scandura, 1977, 1980), these same comments apply to methodology as well. Indeed, "the paradigm shift we have heard so much about in cognitive psychology in recent years is at least partly a myth. True, in our theorizing we have begun to ask HOW and WHY—and not only WHAT a person will do. Rather than developing methodologies to fit the problem, however, we have all too frequently taken the easy but less profitable route of applying methodologies developed for other purposes (Scandura, 1980, p. 389)". Fortunately for the future, an increasing number of studies and content-specific cognitive theories have adopted, either explicitly or implicitly, structural learning methodologies and/or belong to the class of structural learning theories.

References


