COGNITIVE INSTRUCTIONAL PSYCHOLOGY: SYSTEM REQUIREMENTS AND RESEARCH METHODOLOGY

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The following paper does not deal with computer-based instruction (CBI) in the usual sense. Instead, it deals with a body of theory and research which I believe has potentially profound implications for the design of CBI generally. The paper begins with an analysis of the requirements of instructional theory along with a proposal that structural learning theories meet these requirements. Then, the essentials of such theories are illustrated in the context of designing a simple instructional unit on column subtraction. Finally, building on this background, structural learning theories are described more generally and contrasted with other cognitive theories. Implications for computer-based instruction are presented in an epilogue at the end of the paper.

Few educational psychologists take seriously anymore the contention that instruction is simply a technology based on S-R learning theory, as many did during the 1950's and 1960's. Yet today, many academic psychologists (including a high proportion of converted S-R associationists) are trying to convince us that cognitive psychology is the new deity, all the while falsely proclaiming originality and reinventing problems that have already been solved (e.g., see Scandura 1977b, pp. 490-536, 1977c, 1980; Tennyson, 1981). Having spent 20 years studying the subject, my concern is certainly not with cognition per se. My concern lies at a deeper level: Among other things, I am concerned about basic expectations. In experimental psychology, the traditional tendency has been to devise special purpose theories, to study particular problems individually as if they could be understood in isolation, independently of other aspects of human functioning. The implicit belief is that the whole (of human functioning) will become transparent once enough different subareas have been understood: phonics, working memory, semantic memory, problem solving, and so forth. This step-by-step approach to behavioral science might aptly be characterized as "bricklaying." In my opinion, any attempt to understand something as complex as the instructional process by studying the pieces would be at best presumptuous. Without equal attention to the overall architecture, to interrelationships among the parts, piecemeal accumulation is more apt to result in a pile of bricks than in a functioning structure. We need to consider not only cognition and other components of the instructional process but also the interrelationships among these components in the context of dynamic interactional systems.

The main purpose of this paper is to show that what we need in education is not just more empirical research or warmed-over versions of theories developed by our brethren in cognitive psychology — or for that matter, theories in any specialized academic discipline. For too long, instructional research has looked to others for its intellectual nourishment. If the study of instruction is to become a viable discipline, if we are to have viable instructional theories, practical theories that elucidate, then we would do better to build them from within than to wait for others to lead the way. Any viable theory of teaching and learning must first include some way of specifying what must be learned, that is, some way to represent competence. Second, it must elucidate the processes by which people use, acquire, and modify their existing knowledge. Third, there must be some way to find out what individuals know at any given stage of learning, including a way to determine their initial knowledge. Fourth, a fully adequate theory of teaching and learning must allow for the growth of knowledge over time as learners interact dynamically with a changing teaching environment. Finally, the theory must work: To borrow an old cliche, there is nothing so practical as a good theory.

In the following pages I shall show first how the Structural Learning Theory (e.g., Scandura, 1971a, 1973, 1977b, 1980) may be used in designing effective and efficient instruction. Then I will briefly summarize some of the more important features of the general theory — as it pertains to instruction. In the process I shall briefly summarize some of the recent theoretical and empirical progress that has been made to date based on this approach. Finally, building on this background I shall contrast basic features of the approach with those more traditionally associated with cognitive psychology.

BACKGROUND

In my earliest research, I (Scandura, 1962, 1964) found that it is essentially impossible to obtain reliable data on the roles of expository and discovery modes of instruction, no matter how precisely one attempts to specify instructional treatments. More critical than HOW information is imparted is WHEN that information is given in relation to what learners know at the time. If presented too early, pupils not only were unable to use the information, but they also learned gradually not to attend when presented with subsequent information. Given what seemed to be an inadequate S-R language and unnecessarily cumbersome computer programs, I turned my attention in the early and mid-1960's toward the development of a simple but suitably general scientific language for theorizing about such phenomena. Others during that period, most notably Gagne (1965), also were concerned with clarifying relationships between simple S-R and more complex kinds of learning. However, rather than attempting to represent rules, problem solving and other forms of complex learning as complications of S-R learning, it seemed to me more parsimonious, more precise, and more useful to take the rule...
as basic and to explain simpler types as special cases (Scardua, 1967a, 1970b). (The term “rule” denotes a theoretical construct consisting of a domain, a range, and a restricted type of procedure, and is further discussed below.)

During the 1960’s, my students and I used RULES in the analysis and empirical study of a wide variety of behavioral phenomena, ranging from simple to complex (many of these studies are summarized in Scardua, 1969, 1976). The rule construct was subsequently adopted in research by a number of influential educational psychologists (e.g., Gagne, 1970; Merrill, M.D. & Boutwell, 1973) and apparently it is now widely accepted (Merrill, P.F., 1978; Schmidt & Gerlach, personal communication).

The Structural Learning Theory (Scardua, 1971a) is a natural extension of this early work and provides a unifying theoretical framework within which to view the teaching-learning process. In fact, “The Theory” is not really a specific theory at all but rather a CLASS of content and population specific theories. The Structural Learning Theory, however, is not simply a scientific language. Very definite assumptions are made about how and why people behave as they do. Furthermore, numerous specific realizations of the theory have been detailed and empirically tested to good effect (e.g., Scardua, 1971a, 1973, 1977b; Scardua & Scardua, 1980).

AN INSTRUCTIONAL STRATEGY

Certain important aspects of structural learning theories are perhaps most easily seen by example. Hence, we first show how to use structural learning principles in designing instruction on a simple class of tasks.

In order to utilize structural learning principles in designing instruction, the ESSENTIAL first step is to identify: (a) the educational goals — what the learner is to be able to do after instruction and (b) prototypic cognitive processes or rules — what the learner must learn if he is to perform successfully on tasks associated with the educational goals (e.g., Scardua, 1971a). Thus, for example, educational goals may vary at one extreme from something as specific as “saying cat when shown a cat” to something as broad as “being able to devise an operational theory to explain any given set of behavioral phenomena.” (In this regard, it is not essential to specify each and every criterion task, only to be able to distinguish given tasks that qualify from those that do not. Note also that prototypic processes may be specified by the teacher or via behavioral research.)

In structural learning theories what must be learned is one or more RULES. In such theories, rules are theoretical constructs which may be used to represent all kinds of human knowledge. A Rule consists of a domain or set of encoded inputs to which it applies, a range or set of undecoded outputs which it is expected to generate, and a restricted type of procedure which applies to elements in the domain.

For example, consider a rule for adding “ed” to verbs. In this case, the domain of the rule is the set of all verbs to which “ed” can be added. The range of the rule consists of the resultant verbs (i.e., the verbs with “ed” added, properly spelled). The procedure of the rule may be described as follows:
1) If the last letter (of the verb) is a “s”, then add a “ks” and then “ed”.
2) Otherwise, if the last three letters are of the form consonant-vowel-consonant, then double the final consonant and add “ed”.
3) Otherwise, if the verb ends in “e”, then drop the final “e” and add “ed”.
4) Otherwise, if the last letter is “y” preceded by a consonant, then change “y” to “i” and add “ed”.
5) Otherwise, just add “ed”.

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 educational goals in question. In the case of simple subtraction, this sample might include such problems as:

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<thead>
<tr>
<th>9</th>
<th>879</th>
<th>432</th>
<th>402</th>
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<tbody>
<tr>
<td>5</td>
<td>325</td>
<td>129</td>
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<td>?</td>
<td>???</td>
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The second step in structural analysis involves determining the scope of each selected problem and identifying rules for solving each type. 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 remainder of any analysis will be adequate just to the extent that these assumptions are applicable to individual students in any given target population.
(b) The analyst must decide the scope of each of the sample (prototypic) problems. This scope effectively defines the domain of the rule associated with each prototype. The problem

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</table>

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.

Figure 1. Subtraction Rule (algorithm) and sample subtraction problems.
(c) Next, the analyst must identify the cognitive steps (operations and decisions) involved in solving each of the representative problems. These operations and decisions must be sufficiently simple that using them requires only encoding/decoding abilities that are assumed available to ALL in the target population. 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, incorrect use, of failure.

The flow diagram in Figure 1 depicts the procedural portion of a rule based on borrowing, more commonly known as the "borrowing algorithm." Notice that each operation of this procedure acts only on digits, rows, and columns—illuminating the need to assume certain minimal encoding/decoding abilities. The decisions of this procedure (e.g., Is top number greater than or equal to bottom number?) constitute additional assumptions concerning minimal cognitive ability. In turn, the operations (e.g., change 0 to 9, subtract using basic facts) must be other known perfectly or not at all. According to the Structural Learning Theory, 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.

Much more can be said about the actual processes by which rules are constructed but this area is currently the focus of considerable research and going 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 structural analysis of the subject matter in question. Notice, in particular, that I have said nothing about a taxonomy of subject matter content: unlike behavioral approaches to instructional design (e.g., Gagne, 1965), ALL content according to the structural learning perspective must be analyzed.

**INSTRUCTIONAL STRATEGIES**

Once a structural 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 objectives (e.g., solve arbitrary column subtraction problems) and (b) what the student must learn in order to be able to do that.

Given this information, the first thing one must do in designing an effective instructional strategy is to determine what each student already knows, specifically, which parts of the to-be learned rules that the student knows. The testing process by which this is accomplished has been detailed earlier (e.g., Scandura, 1971a, 1977) and is not considered here. For present purposes it is sufficient 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, and there are only a finite number of different paths associated with any given rule.

Moreover, given the above assumption of atomicity (of basic operations and decisions), success or failure on any one problem associated with such a class provides complete information as to the availability to the student of the particular path in question. For example, the problem

\[
\begin{array}{c}
879 \\
-325 \\
\hline
???
\end{array}
\]

is solved by following the path defined by operation one, then two, then three, and back to two, 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 he does not know. Such testing, in effect, defines the student's entering level. It is sufficient for this purpose to test each subject on one randomly selected item from each equivalence class, for according to our atomicity assumptions, success on any item implies potential success on all other items from the same equivalence class.

**PRESCRIBING INSTRUCTION**, then, follows directly from what the student knows. All one needs to do is identify the missing portions of the desired subtraction rule and to present them to the student. The theory is neutral on how this information should be presented (e.g., by exposition or self-discovery) since this depends on secondary objectives of the instruction (e.g., to improve verbal processing or discovery techniques).

As an illustration, suppose a student's knowledge may be represented by the flow diagram shown above, minus only the loop involving operation six (change 0 to 9). In this case, the instructor would need only to make sure that the student knows how to test whether the top number in a column is zero, how to change zero to nine, and how to proceed to the next column (operation five) at the appropriate points. Where a student knows less one would start with simpler prototypes (partial rules representing what the student knows) and gradually elaborate, or add increasing detail until the student has mastered the entire rule.

The close relationship between instructional strategy and basic underlying theory has a number of other important advantages, not the least of which is the integration of what sometimes appear to be different concepts. In more taxonomic and/or pragmatic theories, for example, a distinction is frequently made between MACRO and MICRO instructional strategies (e.g., Reigeluth & Merrill, personal communication). Viewed from our theoretical perspective, this distinction is totally arbitrary and depends solely on the preferred level of analysis. The point is that individual atomic rules are themselves simply rules. They, too, may be "broken down" into still more basic components. For example, operation 2 "Subtract bottom no. from top no. using basic facts" may (and with respect to many student populations SHOULD) be represented in more detail in terms of the individual facts involved.

In this case, the instructional strategy for teaching operation (rule) two would be identical to those used with other rules, namely, start with the known paths and elaborate.

In concluding this section, it must be emphasized that the above illustration of prescriptive aspects of structural learning theories constitutes only a simple prototype. It 'epitomizes' the prescriptive theory in this sense. The theory itself provides a far more generalized basis for instructional prescription, which in principle may be used with any subject matter that might be of interest — no matter how complex that subject matter, and, if improving instructional efficiency rather than theoretical completeness is the goal, no matter how unstructured.

**OVERVIEW OF THE GENERAL THEORY**

In the general theory (as applied to instruction), "content" is effectively characterized in terms of tasks or problem situations that the teacher wants the learner to master, and is referred to as the **PROBLEM DOMAIN**. The prototypic processes (rules) that collectively make it possible to solve problems in a problem domain are referred to as **RULES OF COMPETENCE**. Collectively, the set of competence rules is called a **COMPETENCE ACCOUNT** of the problem domain and constitutes what the learner must learn in order to master the "content". (Note: With very complex domains, a competence account may not and normally will not be complete. The goal of structural analysis is to come up with the most complete and efficient account feasible.)

In structural learning theories the competence underlying any given problem domain is represented in terms of a finite set of rules. These underlying rules must be represented in sufficient detail that all of the specified components make direct contact with assumed minimal capabilities of (all) students in the target population. Specifically, these components must be either uniformly available or atomic as explained above. (In general, inferences drawn about cognitive processes from observable behavior necessarily involve both encoding/decoding and internal processes — in a combination that cannot be determined via observation alone. Specifically, a theorist may equally well absorb most of the explanation into the encoding/decoding (of static structures) or into internal cognitive operations. (See Anderson, 1975; Scandura, 1980, footnote 5, 1981a for further discussion.)
In order to generate solutions to given problems, it is not necessary to have a solution rule directly available. Rather, in structural learning theories solutions may be generated indirectly since rules are allowed to operate in higher-order fashion; they may operate on other rules to generate new rules. The new rules, in turn, may generate the solutions (e.g., Scandura, 1971a, 1980).

The explicit introduction of higher-order rules has a number of important general advantages: (a) Higher-order rules represent interrelationships in a way that appears to allow for "creative potential" (that is, unanticipated outcomes). In addition, the introduction of higher-order as well as lower-order rules often makes it possible to account for relatively complex domains in an unusually efficient manner (e.g., Scandura and Durnin, 1977). (b) As discussed below in the section on THE LEARNER, higher-order rules appear to provide a general and viable means for representing human knowledge. Moreover, control assumptions concerning interactions among rules are highly consistent with what is known or can be profitably inferred from observed systems (Erl, 1961). In addition to simply combining lower-order rules, the higher-order rules identified in this study dealt directly with logical inference, analogy, generalization, and the generation of subproblems.

Another study, by Scandura and Durnin (1977), dealt with these limitations. Specifically, twenty-four lower-order and higher-order derivations and problem-definition rules were shown to be adequate for proving all 130+ theorems and proof exercises in an experimental high-school text on number systems (Brunsfel, Eicholtz, & Shanks, 1961). In addition to simply combining lower-order rules, the higher-order rules identified in this study dealt directly with logical inference, analogy, generalization, restriction, and the generation of subproblems. The study reported in Scandura et al. (1974) was limited in another important respect. The rules identified, including the higher-order rules, were of varying degrees of complexity. A later study by Wulfreck and Scandura (1977) demonstrated that this limitation could be overcome simply by repeating structural analysis until all rules consisted of such molecular operations as setting a compass and using a fixed compass to construct an arc. Not only did this analysis result in simpler rules individually but the rule set as a whole had qualitatively more generating power as hypothesized by Scandura (1973, p. 116). The resulting theory was implemented on a computer and used as a basis for generating theoretically optimal learning sequences for each individual. These proved to have a two-to-one advantage over learner-controlled and random sequences. Scandura and Scandura (1980) further demonstrated the applicability of structural analysis to what are normally considered "unstructured" domains. Specifically, structural analysis of Piagetian conservation tasks provided a (partial) characterization of competence at two different stages of cognitive development, the concrete operational and the pre-operational, and of the transition between them. This analysis also provided an explicit basis for teaching pre-operational children to conserve in a manner difficult to distinguish from that of natural conservers. Equally important, it was possible to manipulate "horizontal decalage" (both positive and negative transfer) in individual children, something which has been difficult to explain, let alone predict or control within Piagetian (and other) Theory.

EMPIRICAL RESEARCH USING STRUCTURAL ANALYSIS

To date, my collaborators and I have completed several major structural analyses. Our first attempt in this direction was a very practical endeavor, developing a workbook based on rules to parallel a recent text (Scandura, 1971b). Ehrenpreis and I (1974) found that almost half of the lower-order solution rules could be eliminated as redundant by introducing a set of just nine higher-order rules. Moreover, a subsequent empirical investigation demonstrated the viability of this analysis. Two groups of elementary school teachers were taught either a subset of 304 lower-order solution rules (D group), or 164 solution rules and 5 corresponding higher-order rules (H group). The results showed that: (a) The subjects learned all rules to a high degree of proficiency, (b) The H group performed as well on tasks requiring the derivation of solution rules as did the D group which had been trained on these solution rules directly, and (c) The H group performed better on transfer tasks for which neither group had been trained.

In another project Scandura, Durnin, & Wulfreck (1974) conducted a more intensive analysis of geometry construction tasks. Among other things this study demonstrated that the heuristics identified by Ploya (1962) can be sufficiently detailed that children can be taught to use them both successfully and reliably.

A subsequent empirical analysis (Scandura, Wulfreck, Durnin, & Ehrenpreis, 1977) demonstrated that the higher-order rules provided an adequate basis both for diagnosing individual strengths and weaknesses in problem solving ability and for overcoming these weaknesses. In particular, instruction on the higher-order rules made it possible for students to solve new problems that they had never seen before. Moreover, they got progressively better at learning new higher-order rules. In this study, predictions could be made with far greater precision than in the Ehrenpreis and Scandura (1974) study. Specifically, the predictions referred to individual performance on specific problems rather than just to group averages.

In spite of these encouraging results, the Scandura et al. (1974) analysis was limited in some important ways: (a) logical inference was not included in the analysis, (b) all higher-order rules served to compose (join sequentially) other rules, and (c) no distinctions were made between deriving solution rules and breaking problems into subproblems.

THE LEARNER

In structural learning theories, it is assumed that what an individual does and can learn in any particular situation depends directly and intricably on what he already knows. More particularly, it is assumed that human cognition may be adequately characterized in terms of specific individual knowledge (represented in terms of rules) and universal characteristics of the human information processor.

Clearly, instruction is concerned primarily with individual knowledge. From an instructional point of view, universal characteristics are best thought of as those aspects of human cognitive functioning which are inherent to man generally; they need not, and in some cases cannot, be taught. Nonetheless, universal characteristics impose important constraints on the way knowledge may usefully be represented and measured. They also determine what may be learned under what circumstances and, hence, play an important, if indirect, role in instructional theory.

Two universal characteristics of human cognition may be assumed in structural learning theories: One pertains to control (allowable interactions among rules) and the other to processing capacity and speed.
used in particular situations, by "goal switching" or more accurately by deepening the level of rule search (Scandura, 1980, 1981). In structural learning research, unlike that in most cognitive psychology, control mechanisms have themselves been the subject of direct empirical study (see Scandura 1971a, 1973, 1974, 1977b).

This research has demonstrated that a wide variety of behavioral phenomena, ranging from problem solving and learning to motivation, memory and skill development (automatization), may be understood and predicted by assuming the following control mechanism: When confronted with a problem the learner is assumed to check the rules available (e.g., in working memory) one by one to see if they apply (i.e., as determined by a very specific test of the rule's domain and range). If exactly one such rule is found, it is actually applied. When no solution rules are immediately applicable, or when there is more than one, the search moves to the next level to check for higher-order rules which have the potential to generate a unique solution rule that applies, and so on as necessary. 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.

For example, in the first of a long series of experiments 1 (1971, 1974) trained 24 young children on simple rules of the form A→B and composite rules of the form A→B→C (where A, B, C, etc. were objects to be identified 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→B, B→C), generated corresponding composite rules of the form A→B→C.

If this information, specifically A→B and B→C rules, and the higher-order rules, had been programmed into a computer and then it was presented with the problem (A→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 preequipped with an adequate control mechanism. Nonetheless, the children who had been trained on the higher-order, as well as the other rules, ALL succeeded on the crucial test problem. Those who were not trained on the higher-order rule uniformly failed.

These results and many others like them (e.g., Scandura, 1977b) indicate two things: (a) Even young children come "wired in" with something equivalent to the postulated goal-switching control mechanism. 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 reverted to the original level and the newly found 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 (e.g., Newell & Simon, 1972), is too strong an assumption. Such a mechanism would not be universally available to ALL people and, hence, would be of limited utility in explaining human cognition.

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

Processing capacity is the second hypothesized cognitive universal (Scandura, 1971a, 1973; Voorhis & Scandura, 1977). In contrast to most cognitive theories, working memory in the Structural Learning Theory is assumed to hold not only data (the stuff on which rules operate) but rules (processes) themselves. This difference has a number of important implications pertaining to a variety of memory phenomena (e.g., Scandura, 1973, 1978), only some of which have been investigated empirically.

For example, while capacity per se is assumed to be fixed (although it may vary over individuals), the memory load associated with any given task depends directly on the process (rules) used in solving it: the "chunks" (e.g., Miller, 1956) that are effectively operating at each point in time are defined dynamically by the rules in question as they undergo execution (see Scandura, 1971a, 1973, Chapter 10). Thus, while it may be impossible to multiply large numbers in one's head using the standard algorithm, many people know short-cut processes (e.g. for numbers ending in 5 or 0) that enable them to do so.

In effect, knowing how to do something is not always sufficient; a considerable degree of skill also may be important. In this regard, let me just mention that the transition from neophyte (knowing how) to master (knowing well) may be explained in terms of the postulated control mechanism and higher-order automatization rules (e.g., Scandura, 1973, 1981). The latter serve to absorb procedural complexity (of input rules) into domain structures (of output rules). This has the effect of reducing response time in applying output rules by shifting the problem solving burden from procedural computation to finer stimulus discriminations (Scandura, 1981; also see Scandura & Scandura, 1980).

In the theory, the concepts of memory load and processing speed are closely related (Scandura, 1977b, Chapters 2 and 7). Specifically, in order to account for processing speed (i.e., response latency minus encoding and decoding times), as well as the responses themselves, the underlying rules must be represented in considerably more detail (than when concerned only with the responses). For example, predicting the time it takes to generate the sum of two numbers requires that the rules not only be represented in terms of components that are atomic in a behavioral sense, but also that these components be sufficiently fine-grained as to require equal processing times. (Such components are called "process atomic," Scandura, 1977b, pp. 111-135.)

In general, the desired level of behavioral precision determines which universal characteristics and which level of (knowledge) representation is required in a structural learning theoretic account of the phenomena. Specifically, two levels of structural learning theories are readily distinguished. At the behavioral level, such theories involve only the control mechanism and rules represented in terms of behaviorally atomic components. Theories at this level make it possible to predict individual responses but they are silent on the issue of processing time. They are, in effect, idealizations that fit reality only to the extent that processing capacity is not a factor (e.g., see Scandura, 1977b, 1978, pp. 152-155). To the extent that processing capacity is involved, theoretical predictions may be expanded to deviate from obtained results. Nonetheless, research has shown that behavioral level theories are quite adequate for most instructional purposes. Indeed, they provide far more detailed accounts of student behavior than do traditional normative studies (e.g., Scandura, 1977d).

At the second or process level, structural learning theories involve the control mechanism, processing capacity, and process atomic rules. As a consequence, theories at this level can validly be tested under less stringent conditions. Correspondingly, they deal with latencies and, hence, provide more detailed accounts of behavioral phenomena.

Increasing the range of applicability obviously does not come without a price: given equivalent levels of task complexity, process level theories are relatively more difficult and exacting to construct. Thus, although traditional cognitive psychology is replete with theories that predict latencies, few satisfy the aforementioned structural learning constraints. Among those that appear closest are the chronometric theories of simple arithmetic by Groen and his associates (e.g., Suppes & Groen, 1967) and the computational theories of Voorhies and Scandura (in Scandura, 1973, Ch. 10, 1977b, 1978, pp. 155-166).

ASSESSING INDIVIDUAL KNOWLEDGE

In contrast to universal cognitive constraints, specific knowledge is assumed to vary over individuals. As described above, the theory
shows how prototypic competence (i.e., rules of competence prototypic of given populations) may be used to operationally define the knowledge available to individual members of such populations. Specifically, the theory tells how, through a finite testing procedure, one can identify which parts of which rules individual students know (and do not know). Rules of competence serve in a very real sense as rules of measurement and provide a sufficient basis for the operational definition of human knowledge (see Scarduna, 1977b, Chapter 2).

Individual knowledge (or behavioral potential), in effect, may be represented in terms of rules — specifically, in terms of SUBRULES of given rules of competence. Notice in this regard that the knowledge attributed to different individuals may vary even where only one rule of competence is used to assess behavior potential. For example, if a person succeeds on only one path, then his knowledge would be represented by that path, which is a subrule of the initial one. Where two or more paths are involved, a combination of the paths would be used to represent individual knowledge.

I shall not attempt here to detail structural learning-type assessment procedures since that has already been done in the literature (e.g., Scarduna, 1973, 1977b). Let me just emphasize three key points:

(1) That aspect of the Structural Learning Theory that deals with knowledge assessment is both relativistic and highly efficient. On the one hand, the individual knowledge is measured relative to the prototypic rules of competence associated with a given problem domain and student population, taken collectively. On the other hand, assessment with respect to such a domain is accomplished in a modular fashion. That is, as a consequence of the universal control mechanism, testing with respect to any one rule may be accomplished independently of any other. Furthermore, given atomic assumptions concerning component rules, single test items provide sufficient information as to mastery of corresponding paths of the rule itself. Test efficiency may be increased even more by taking into account the natural hierarchy among paths and the sequential (i.e., conditional) testing this makes possible.

(2) There is considerable empirical support for the general theory. One type of study involved the following: (a) Given a class of tasks, one or more prototypic rules were identified which were both adequate for generating solutions to each of the tasks and compatible with the way a knowledgeable or idealized (prototypic) member of the target population might be expected to solve them. (b) The paths of these rules were used to partition the class of tasks into equivalence classes. (c) Subjects in the target population were tested on two items (tasks) from each equivalence class. (d) Performance on one item from each equivalence class was used as a basis for predicting success or failure on the second item.

With highly structured tasks run under carefully prescribed laboratory conditions, it has been possible, given performance on the initial items, to predict performance on new (second) items with over 96% accuracy (e.g., Scarduna, 1973; Scarduna and Dunn, 1977). When testing took place under ordinary classroom conditions, with the subjects run as a group, the predictions were accurate in about 84% of the cases (e.g., Dunn & Scarduna, 1973).

(3) Because the appropriate level of rule representation varies directly with population sophistication (and desired level of behavioral detail), it is often practicable to analyze even complex task domains (at a level of analysis that is sufficient for assessing the behavior potential of individuals in the population).

INSTRUCTIONAL SYSTEMS

It is not easy to reduce complex and sometimes subtle interrelationships to linear form (as in writing). I have, nonetheless, tried in the above sections to stress some of the more crucial interrelationships which exist among content, cognition, and individual differences in the context of instruction.

In each area we have seen that the choice of representation (i.e., the theoretical constructs, their characterization, and their mode of operationalization) is crucial. Specifically, the rule construct was defined as it was (i.e., as a triple consisting of a domain, a range, and a restricted type of procedure) to meet certain very critical requirements that appear essential in any viable theory that deals with individual behavior in specific situations.

Thus, the above method of operationalizing individual knowledge (i.e., for assessing individual behavior potential) depends crucially on both the restrictions placed on the procedures (operations) of rules and the aforementioned assumptions concerning encoding and decoding. Although this is not the place to dwell on technicalities, the procedures in question are restricted to those that can be represented concretely as nonrecursive structured programs (e.g., Haskell, 1975; Aalig & Arbib, 1978). Unrestricted procedures allow for the generation of new (sub)procedures and their subsequent use in executing such procedures (i.e., recursion). In effect, goal switching in unrestricted procedures, rather than being distinguished from specific competence, is intertwined with it. This confounding leads to unnecessarily complex procedures, which seem to have little heuristic power in so far as individual differences measurement is concerned.

At the other extreme, the operations of simple productions (e.g., see Post, in Minsky, 1967) are too restrictive. Productions disallow the possibility of internal decisions and effectively act as atomic rules. While the necessary richness might be obtained by introducing sets of productions (i.e., production systems, Newell & Simon, 1972) to represent competence, doing so destroys much of the heuristic value gained by representing competence in terms of rules. Independent justification for this observation can be gleaned from the fact that, although Siegler and Klahr (e.g., Klahr, 1978), for example, have used production systems in much of their work, the (finite) decision trees they used for diagnostic purposes are, in fact, rules. When represented in terms of production systems, the underlying processes appear to lose their heuristic power almost entirely. In effect, although there are any number of scientific languages that are sufficiently rich to characterize cognitive competence, formal equivalence is not the same as psychological equivalence, even less so when the needs of instruction are taken into account.

The above restriction on the procedures of rules is made possible by the cognitive separation between specific knowledge and control, which in turn is made feasible by strongly supporting data which suggests the universality of goal-switching control. This separation of specific knowledge and control has the effect of extracting goal-switch procedures from unconsciousness. In summary, restricting the procedures of rules, together with the encoding/decoding assumptions referred to previously, greatly simplifies the representation of competence without reducing generality. These constraints "force" competence into a form that is unambiguous (relative to encoding/decoding assumptions) and that considerer heuristic power insofar as operationalizing individual knowledge is concerned.

Other features of the rule representation are equally crucial. For example, adding ranges (to rules), that are INDEPENDENT of the domains and the procedures plays a crucial role in goal-switching control. Given the assumption that people may be characterized as goal-directed information processors, it stands to reason that rule-use depends on what the knower expects rules to do and not just on how and where they can do it. What a person expects a rule to do is not necessarily what the rule will actually do: for example, in tightening a joint, a plumber might expect (hope?) to stop a leak but actually cause the pipe to break.

Goal-switching control, in turn, not only has found strong and direct empirical support in its own right but it also provides a pragmatically useful basis for identifying what must be learned in instructional situations. Thus, the separation of specific knowledge/competence control greatly simplifies the task of dealing with high level interrelationships that are frequently involved in analyzing complex domains. Specifically, taking the control mechanism as given not only makes it possible to represent competence in a modular fashion (in terms of independent rules) but also makes it easier to identify this competence.

In the latter regard, I have been concerned in my theoretical work only in part with specifying constraints on the representation of competence (i.e., representing what must be learned as rules). I have
been equally concerned with the problem of HOW to identify the
competence underlying given problem domains. As a result of
carrying out an increasing number and diversity of structural
analyses, I believe that it may be possible to construct structural
learning-based competence theories in a relatively efficient,

dynamic, and objective manner. This is especially so in the case of
competence theories that are intended to be used for instructional
purposes — but not only in these cases (e.g., see Scarduna &
Scardura, 1980).

In many ways, the problem of how to devise specific competence
theories is more basic than any of the others. Prior structural
analysis of a given body of content, recall, is the essential
prerequisite for realizing particular structural learning theories.
Given an analyzed problem domain, the rest of the theory follows
directly: the assessment of individual knowledge, the specification
of what individual learners will do and/or learn in particular
problem situations and detailed plans for guiding (teaching) the
learner. It is worth emphasizing in this regard that the assumed
universals used to (partially) characterize human cognition and the
proposed assessment, and instructional methods, as with structural
analysis itself, refer to the entire class of structural learning theories
(i.e., to the Structural Learning Theory as a whole) and not just to
particular realizations.

RELATIONSHIPS TO TRADITIONAL COGNITIVE THEORIES

Few behavioral scientists would argue with the general thesis that
any viable theory of instruction must deal with the questions of what
is to be learned, what the learner already knows that might be
relevant (and by implication, what is not known), and how to get the
learner from where he is to where one wants him to be (e.g.,
Atkinson, 1972; Wulfeck & Scarduna, 1977). There are, however,
differences of opinion as to how to achieve these ends.

Cognitive psychology, for example, obviously shares many con-
cerns with the structural learning school. Nonetheless, con-
temporary research in the former area rests on traditional assump-
tions which are quite different than those which have guided
developments in structural learning. As we have seen, perhaps most
basic is the fact that developments in structural learning have been
motivated largely (but not exclusively) by system considerations.

In this section I consider some of the more basic points of
difference between structural learning theories and most con-
temporary theorizing in cognitive psychology (cf. Scarduna, 1971a).
First, consider the basic experimental paradigm used to test
traditional normative theories in cognitive psychology: (a) Given a
class of tasks, one or more alternative cognitive theories is proposed
as to how subjects perform on these tasks. Specifically, the theorist
attempts to characterize the processes people go through in solving
the tasks. For example, cognitive psychologists interested in
instructional problems have asked such questions as: How do people
solve problems in arithmetic? How do they read? Etc. (b) Based on
the alternative theories, predictions are made as to how the subjects
should behave on the tasks. (c) Groups of subjects are given the
tasks and their behavior is recorded. (d) Group means (and other
statistics) are computed and analyzed statistically. The results are
then compared with the predictions. (e) Depending on the respective
fits between theoretical predictions and the empirically determined
group means, inferences are made about how people perform on the
tasks (i.e., about the validity of the alternative theories).

Now, it is perfectly proper to do this. It is not, however, proper to
infer that INDIVIDUAL, subjects perform in any given way just
because a theory to that effect has been shown to be consistent with
how groups of subjects perform — on the average. If we have
learned anything over the past millennium it is that individuals do not
always, perhaps rarely, do things in the same ways or with the same
effectiveness. Moreover, the more complex the tasks (i.e., the more
complex the theory needed to account for behavior on the tasks), the
greater the deviation to be expected between normative expectation
and individual reality. Equally important here, the aforementioned
approach to science simply does not provide the kinds of in-
formation needed to make instructional decisions concerning indi-
viduals.

Consider another well-known approach to cognitive science — that
which goes under the rubric of "computer simulation". Unlike
cognitive theories devised by experimentalists, computer simulation
theories do deal with individual processes, both at the theoretical
level and in empirical testing. Thus, for example, predictions are
typically matched with verbal protocols obtained as subjects solve
the tasks at hand. There is also a difficulty in this regard, however.
Specifically, this approach gives too much attention to individual
processes; a different cognitive theory may be required for each
individual.

In effect, contemporary cognitive theorizing is posed with
something of a dilemma insofar as instruction is concerned: In order
to devise theories that deal with individual behavior and, hence, that
might have basic educational relevance, one is forced to devise a
separate cognitive theory for each individual. On the other hand, if
one wants generalizable theories, then one is restricted to normative
behavior — with inferences to the individual being speculative at
best.

In order to achieve these dual objectives, structural learning
theories necessarily reject both normative and idiographic (e.g.,
simulation) approaches as inadequate and adopt a RELATIVISTIC
view of behavioral theorizing. This approach explicitly rejects the
implicit assumption of many cognitive psychologists that we can, in
fact, find out how people ACTUALLY do things. The best we can
hope to do is to characterize individual knowledge in relativistic
terms — relative to predetermined rules of competence.

The precision with which individual knowledge can be specified
depends on the extent and detail of the representation (of prototypic
competence). Beyond a certain point, further discriminations
become immaterial and cannot, in any case, be detected within the
domain in question.

Thus, if one is interested only in success or failure on a given class
of tasks (e.g., subtraction problems), then it makes no difference
whether a subject applies a well-known algorithm or devises and
applies a new solution method. Such possibilities cannot be
distinguished within the domain; this can only be terminated via
performance on extra domain tasks — or, equivalently, by
redefining the domain of interest. (Note: Where redefinition is
required or desired, it is NOT necessary to start over with a new
structural analysis. Rather, one begins with the results of the given
analysis and continues the process, e.g., see Scarduna, 1974a).

In addition to our work and that of others consciously working in
structural learning, the potential of using cognitive prototypes as in
structural learning theories is evidenced by the fact that several
investigators in the United States (e.g., Siegler, 1978; Klahr, 1978)
have recently used such theories in their diagnostic studies of
children’s learning. In addition, “Hypothesis Theory,” as
developed by Marvin Levine (1966) to include probes for diagnostic
testing, also is a structural learning theory restricted to particular
kinds of simple discrimination learning tasks. Overseas, Landa
(1976) developed a more general diagnostic method in the sense that
it generalizes over content as does that referred to here. As with
others, however, his method is limited to situations where the
underlying rules of competence have a simple (finite) tree structure.
In effect, all of these applications are restrictions of that outlined
above (where unrestricted looping is allowed) — all employ special
cases of the general diagnostic theory, albeit sometimes without

Second, from our discussion of the Structural Learning Theory we
have seen that those aspects of the theory involving content,
cognition and individual differences are all interrelated.

The representation of competence — or of what must be taught, for
example, was dealt with in a way that was consciously sensitive to
the requirements for testing, and to what is known about how
people use their available knowledge. Specifically, the represen-
tation of knowledge in terms of rules (and the structures on which
they operate) was shown: (a) to be fully operational (i.e., to lend
itself to the assessment of individual knowledge, or behavior
potential, relative to given competence — as opposed to norms) and
(b) to be consistent with general constraints on cognitive processes imposed by the nature of the human information processor.

Third, the relevance of existing cognitive theory becomes even more problematical when it comes to questions of what is to be learned and problems of instruction per se. In the former regard, the distinction between what is to be learned and what the learner knows is typically confused in existing cognitive theorizing. This lack of distinction, ironically, may derive, in part, from the traditional distinction (originating in psycho-linguistics) between competence and performance. Recall, in this regard, that COMPETENCE was equated with idealized grammar (e.g., with theory for generating sentences in a language). PERFORMANCE, on the other hand, refers to what human subjects are actually capable of.

Aside from issues pertaining to type of representation, the traditional notion of competence is quite compatible with the characterization of what is to be taught. The situation is not so direct with performance, however. For one thing, recall the complications due to the individual/normative considerations I have already raised. (Also see Scandura, 1977b.)

For another thing, and more important here, a major distinction in structural learning theories is confounded in the traditional view. Specifically, performance depends on both specific individual knowledge and cognitive universals. It is important, I think, to maintain this distinction in any viable theory of instruction. While instruction is and can properly be directed toward individual knowledge, this is not the case for cognitive universals.

Four, closely related to this confounding, is the question of methodology. Clearly, the methods used in experimental psychology may be very useful, and indeed may be indispensable for some purposes — like finding normative theories of average behavior. They are, however, neither exhaustive, indispensable, nor perhaps even desirable for purposes of studying the instructional process. While the traditional experimental approach may provide reliable information in the laboratory, this has far less frequently been the case in instructional settings. Furthermore, the normative information provided may bear little relationship to the prototypic competence that one might want to teach. Even suppose that such an approach did yield reliable and instructionally valid information: The approach would be so inefficient, in view of the time and expense required to conduct such studies and the large variety of content that might be taught, as to be almost useless for instructional purposes.

For instructional purposes we need to develop systematic and efficient methods for the identification and evaluation of the prototypic competence characteristic of various populations (e.g., culture types) and underlying arbitrarily given bodies of content. (See the Epilogue for recent progress in structural analysis.) In so far as the evaluation phase is concerned, the basic structure of methodology has been reasonably well established (Scandura, 1971a, 1973, 1977b; Durnin & Scandura, 1973; Scandura & Durnin, 1978).

As noted previously, different methods also are needed for the study of cognitive universals (Scandura, 1971b, 1973, 1977b). In this regard, Resnick and Glaser (1976) appear to have followed our lead in their work related to the "invention" problem. Among other things, for example, they attempted in their studies to approximate "memory-free" conditions in their training and have utilized a variant of "goal-switching" in guiding subjects' problem solving. In these studies, however, the problems all could be solved via simple composition of lower order rules (much as in our A→B, B→C, then A→C paradigm) and no attempt was made either to identify or to teach the higher-order rules involved. (For a discussion of the relationships between their work and ours, see Scandura, 1977b, pp. 504-514.)

Five, few cognitive psychologists would imply that their theories deal directly with educational values, instructional costs, or teaching strategies, and perhaps at best indirectly with respect to different types and modes of instruction. What perhaps is not appreciated fully, however, is that instructional strategies can and eventually must constitute a serious theoretical subject. It is not necessary or sufficient to rely solely on intuition, mathematical considerations, or empirical trial and error. While discussion of instructional strategies in the context of structural learning theories is beyond the scope of the present article, and while complete solutions are not yet available, some promising beginnings have been made in this direction (Scandura, 1977a, 1977c; Wulfeck & Scandura, 1977). These advances draw heavily on the foundations outlined above.

CONCLUSIONS

Generations of insignificant and/or non-replicable research on instruction make it clear that global reference to expository, discovery, and other instructional methods will never provide a sufficient basis for instructional decision-making (Scandura, 1962, 1964). Attempts to "match" global instructional methods with generalized learner capabilities appear to have met the same fate (e.g., Cronbach & Snow, 1977). It is now widely agreed that reliable decision making in the instructional arena will require direct reference to underlying cognitive operations (Snow, 1978; Merrill, 1978).

The preceding analyses make clear, however, that not just any cognitive theory will serve instructional needs. Close interrelationships exist among the constructs and assumptions used to characterize what is to be learned, the learner, and 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. Stated more boldly, any cognitive-based and operational instructional theory that deals with individual behavior in a generalizable way will necessarily be a structural learning theory. Moreover, such theory will be complete just to the extent that it satisfies the constraints associated with the Structural Learning Theory. In general, these constraints pertain to the way competence is represented, the operationalization of individual knowledge, and cognitive universals.

While strong, these assertions are meant to be taken seriously. Indeed, irrespective of the validity of my own arguments, the Structural Learning Theory is illustrative of the type of theory needed if behavioral science is to provide stable and reliable understandings. As stated by Booth (1978),

"Mature science is characterized by its inclusion of the style of theory that specifies a system of processes which computably behaves as a whole like the real system, but in addition the individual processes and relationships between them are formally equivalent to processes independently observed to be operative in the real system. Such a systems analysis is genuinely explanatory, and resolves the polarity between reduction and holism."

It should be emphasized, however, that the Structural Learning Theory is central with respect to many specific phenomena. The point is that specific theory, if it is to meet the above conditions, may NOT be inconsistent with established tenets of the Structural Learning Theory. As noted previously, the recent literature includes a growing number of such theories, both our own and those of others. Those mentioned above in the course of our discussion represent only a small sampling.

Theory, however, does not tell the whole story. Equally, if not more important, the aforementioned needs of instructional theory call for different research methodologies. In effect, it is not cognitive psychology per se that I am concerned about. We need to know a lot more about cognitive processes and must support good research directed to that end. What I am concerned about is the uncritical acceptance and maintenance in cognitive research of a research methodology originally motivated by S-R empiricism — even more so by the attempt to foist that methodology on the scientific study of instruction.

In this regard, I would propose that the paradigm shift about which we have heard so much in cognitive psychology is largely a myth. True, in our theorizing, we have begun to ask how and why — and not only what will a person do. Rather than developing methodologies to fit the problem, however, I think unfortunately we have all too often taken the easy but less profitable route of applying a methodology developed for other purposes.

What I am arguing here is that we need new research
CHAPTER 10

Cognitive Instructional Psychology

methodologies as well as new problems and theories. Specifically, in instruction we need to look at competence more in terms of prototypes than as bases for direct prediction of averaged human behavior. If we can adopt this shift in outlook, then as instructional scientists, I believe that we will be in a position — not only to progress more rapidly in instructionally valid directions, but also to say more about individual behavior in specific situations, and most importantly, to be able to do something about that behavior.

EPILOGUE

As we have seen, structural analysis of task content is an essential first step in designing instruction. Given the results of such an analysis (i.e., the to-be-acquired rules), the rest of the theory follows automatically. Specifically, it was suggested that the structural learning theory provides an explicit basis both for assessing individual behavior potential and remediation of cognitive deficits. Since this paper was written, we have completed a major project in computer-based instruction (CBI) which builds directly on the structural learning theory and has begun a second. The first project involved implementing a general purpose “RuleTutor” (e.g., see Scandura, 1981). Basically, the RuleTutor includes all of the machinery necessary for diagnosing individual deficits and for providing needed remediation. Since it was designed for commercial application (in arithmetic), it also deals with meaning, meta cognition (verbalization of known processes) and drill and practice, and includes a sophisticated management system.

The RuleTutor, however, is like a skeleton. It can do all of the above but only when used in conjunction with a rule (that is a rule coded in a way understandable to the host computer). In effect, the RuleTutor itself is a general purpose instructional system without content — sort of like an education major with with no subject specific knowledge. Its value, of course, is that one can construct complete, operational diagnostic/instructional systems in any area simply by adding code for that area to the basic RuleTutor.

Nonetheless, as currently implemented (on an Apple II computer), the RuleTutor has two major limitations with regard to existing theory. First, while it can deal with more than one rule simultaneously, no provision has been made for intersections among (higher and lower order) rules — as assumed to occur in more complex learning. Second, completion of an operational RuleTutor requires structural analysis (to identify the rules in question) followed by coding of the rules.

Since my paper (Scandura, 1981) was originally written, considerable progress has been made in “systematizing” structural analysis (e.g., Scandura, 1982, 1984a, 1984b). In addition, we recently have begun designing a man-machine system which automatically will both perform structural analysis and generate a coded version of the rules so identified.

When this system is complete, we will have at our disposal a completely automated CBI development system. The man-machine system will generate the rules needed for any desired area and automatically convert them to code and incorporate this code into the RuleTutor. The result will be a complete and operational CBI system in the new area.

 Accomplishing all this, of course, will require more computing power than is provided by the basic Apple II, but we still expect to complete the project in a microcomputer environment.

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JOSEPH M. SCANDURA


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