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Theoretical Foundations of Instruction: A Systems Alternative to Cognitive Psychology†

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Analysis of instructional systems shows 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 Structural Learning Theory (or, equivalently, to the class of content specific structural learning theories). Equally important, viable instructional theory is shown to call for methodologies that differ fundamentally from those used in traditional (normative) experimentation.

During the reign of E. L. Thorndike, educational psychology was a natural extension of academic psychology. To be sure Gestalists saw it that Thorndike's law of effect constituted only one major approach, but the bonds of marriage were strong. In the period shortly after World War II, on the other hand, what had been viewed as a continuum from laboratory to educational practice had become a chasm—perhaps as well summarized as any by a remark concerning educational researchers often attributed to the late Kenneth Spencer: "Give them all pensions. Let them do anything. But don't let them do research." In fact, Spencer perhaps was one of the more honest practitioners of academic psychology. He was

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under few delusions regarding applicability. Studying the white rat might lead to an understanding of the white rat but with respect to education—who knows!

Nonetheless, much was heard during the late 1950s and early 1960s about the science of learning and the technology of teaching. Unfortunately, many educational psychologists accepted this view uncritically: The kinds of questions we asked, the paradigms we used, and our experimental methodologies all were carbon copies—albeit 10-20 years removed—of those we adopted from our academic brethren.

Few of us take seriously anymore the contention that instruction is simply a technology that might reasonably be based on S-R learning theory of the early 1960s, no matter how elaborate and updated. Yet, today, with varying degrees of conviction, 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 proclaiming originality and largely ignoring the fact that the contemporary motivation for studying cognition came earlier and from elsewhere—including from educational psychology.

Why am I being so hard on cognitive psychology—especially since my own work on rule and strategy learning in the 1960s antedates most of the contemporary empirical work in the area? In fact, I do believe, strongly, that people have minds, that they do think, and that a proper understanding of cognitive processes may be of great benefit in improving understanding of the instructional process. 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. Thus, we have had theories of serial learning and paired-associate learning, of short-and-long term memory, and of all the rest. More recently, we have seen the rise of more comprehensive theories of cognitive functioning, most of which have emphasized the role of memory or of language. Nonetheless, when viewed from an instructional perspective, the basic strategy has been one of “divide and conquer.” The implicit belief has been and still is, I think, that the whole of human functioning will become transparent once enough different subareas have been understood: phonics, working memory, semantic memory, problem solving, etc. This step by step approach to behavioral science might aptly be characterized as one of “bricklaying.”

In my opinion, any attempt to understand anything 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. It is not, then, that I love cognitive psychology less, it is rather that I love instructional systems more. 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 interactive systems.

To see why I feel this way, consider the parallel field of medical research. Specifically, let me relay some of the essentials of the ongoing dialogue I have been having with a friend who is trying to find the cause of emphysema, a debilitating lung disease. Toward this end, he is committed heavily to piecemeal and painstaking experimental research. Oh, he knows about Watson and the double helix and other important and integrating theoretical contributions to biology; but he stubbornly believes that the answers he is seeking will come from highly directed empirical research rather than from more global theoretical insights.

With regard to instruction, my own views are quite the opposite. We have had literally generations of piecemeal empirical research in education but progress has been at best marginal. All too frequently, the findings either have tended toward vacuous truisms or have been nonreplicable.

In any case, this friend and I were discussing the relative merits of theory and research one day when the question arose as to why he felt so confident of his present empirical course. He answered, “because when we find the cause we will know it.” Think about that for a moment! How often is it that we can say on the basis of our empirical research, “Now I know why, precisely why, Johnny can't add, or spell, or read”? Of course, the literature is filled with research that purports to provide answers to such questions but all is partial with very little being definitive. More important, the answers proposed rarely allow us to do much of anything about overcoming these cognitive deficits much less to do it reliably and with assurance.

Consider some of the reasons for this difference. First, a good deal is understood about proteins, human tissues, and sundry other biological details. The basic form of the theory is well established: what needs to be done in the case of emphysema is to devise a specific realization of this basic theory—to show specifically how emphysema may be explained in terms of existing principles and constructs. My friend is banking on the assumption that no basically new theoretical principles or constructs will be needed. His task in this respect is made easier by the fact that many key theoretical constructs are realized in concrete biological materials: cells, proteins, and the like.

Second, emphysema and many other well-known diseases apparently have specific causes which when determined can be treated rather independently of other aspects of the human biological system. (At
"side effects" are considered unavoidable annoyances that are necessary to
effect desired cures.)

This situation simply does not obtain with respect to instruction. There is little agreement among educational psychologists as to what are the basic principles and constructs, much less as to what might constitute an adequate basic theory. Equally important, many of the most important instructional problems cannot be dealt with statically and in isolation. Overcoming educational deficits may involve both testing and teaching in complex dynamic interactions. (Incidentally, it may be worth noting that medical researchers also are now beginning to appreciate how little they know about how complex biological systems operate to maintain health. Such awareness has come about as hoped for breakthroughs failed to materialize, for example, in the well publicized “war on cancer.”)

The main point of this paper is that what we need in educational psychology is not just more empirical research and are not just 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, educational psychology has looked to others for its intellectual nourishment. If educational psychology is to become a viable discipline, if we are to have viable instructional theories, practical theories that will elucidate, then we would do better to build them from within than to wait for others to lead the way. Only when we have accomplished this, I think, will other scientists, and lay people as well, begin to take educational research seriously. The alternative, I think, is to remain, paraphrasing Jackson’s (1977) remarks† “a vast and varied domain of stagnant waters, with a long past and no future.”

In the following pages I shall describe, first, the essentials of what I consider to be a practical and scientifically viable approach to instructional theory. In the process, I will briefly summarize some of the theoretical and empirical progress that has been made to date based on this approach. Then, I will contrast some basic features of this approach with those more traditionally associated with cognitive psychology.

ESSENTIALS OF INSTRUCTIONAL THEORY

Any viable theory of teaching and learning must include, first of all, some way of specifying what must be learned, that is some way to represent knowledge. Second, any viable theory must elucidate the processes by which people use, acquire, and modify 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. In addition, 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.

During the past two decades considerable progress has been made in the above direction. Thus, considerable progress relevant to various aspects of the above has been made in such fields as artificial intelligence (e.g., Minsky and Papert, 1972; Bobrow and Collins, 1975), individual differences measurement (e.g., Glaser, 1963; Hively, Patterson and Page, 1968; Cronbach and Snow, 1977), and cognitive psychology (e.g., Kintsch, 1974; Anderson, 1976), as well as in educational psychology per se (e.g., Gagne, 1962; Merrill, M. D. and Boutwell, 1973, Merrill, P. F., 1978; Glaser and Resnick, 1972; Rothkopf, 1972; Tennyson, 1977).

There also have been important developments in dealing with the instructional process as a whole (e.g., Pask, 1976; Landa, 1976), and with relationships to general systems theory (esp. Pask, 1976). Specifically, significant progress has been made in understanding the interrelationships among content, cognition, and individual differences and in the way they interact over time as a result of instruction.

Global considerations, of course, necessarily play some role, even in the most prescribed research, as does actual human behavior in global systems-oriented theories. Nonetheless, the extent to which “top-down” considerations have influenced the former and the extent to which “hard data” have influenced theorizing about instructional systems have generally been quite limited.

Somewhat orthogonal to the above dichotomy has been the widely sensed gap between theory and practice (see Scandura, Frase, Gagne, Groen and Stolow, 1978). Typically, theories associated with the various academic disciplines have been perceived as having at best peripheral relevance to instruction. On the other hand, pragmatically generated teaching techniques and/or design principles have been largely devoid of theory.

To date, I am aware of only one theory which has seriously probed the "no-man's land" between these alternative views and concerns, that is, Structural Learning Theory (Scandura, 1971a, 1973, 1977b). This theory and a rather large body of supportive empirical research have been well documented in the literature, most recently and comprehensively in my books on Structural Learning and Problem Solving (refs.). I shall not attempt to survey this literature here.† Rather, to provide a basis for

†It is impossible within the space of a few pages to summarize adequately even the main features of the Structural Learning Theory. Early beginnings followed by a large body of related research on rule learning appeared in print as early as 1962 (Scandura, 1962, 1964).
comparison with contemporary theorizing in cognitive psychology, I shall emphasize essential historical, global and methodological considerations, with special attention to relationships to the instructional process.

Historically, development of the Structural Learning Theory was motivated by instructional considerations. Specifically, the goal of my very first piece of serious research (Scandura, 1962, 1964) was to help clarify the roles of expository and discovery modes of problem solving instruction. What I found was that it is essentially impossible to obtain reliable results no matter how precisely one attempts to specify instructional treatments. More critical than how information was imparted was when that information was given in relationship to what learners knew at the time. If presented too early, pupils not only were unable to use the information but also they gradually learned not to attend when presented with subsequent information. This research, incidentally, employed a combination of informal observation and analysis, supported by precise operational definitions and experimental methodology, not unlike that which characterizes much contemporary cognitive psychology.

Nonetheless, although certain analytical tools were used (e.g., the use of algorithms to represent what was to be learned), a major problem with this research was the inability to operationalize individual knowledge. Specifically, it was difficult to tie the phenomena being studied in with the S-R and concept learning studies, or with the computer simulation studies, of the day. Given what seemed to me 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. Rather than attempting to represent rule, problem solving and other complex forms of learning as complications of S-R learning, however, it seemed to me both more parsimonious and more useful to take the rule as basic and to explain simpler types as special cases (e.g., Scandura, 1967a, 1970b). (Equally important, this type of formulation appeared to be considerably more precise, thereby making it possible to avoid certain problems which arise, for example, in attempting to represent rules or principles in terms of concepts or associations, see Scandura, 1967a, esp. p. 339; 1970b, pp. 517-521).

In the Set-Function Language developed as a result of this work, the emphasis was on sets of observable input-output (stimulus-response) pairs and on rule (function) constructs needed to explain how outputs were to be generated from the inputs. Specifically, rules were characterized as triples, each rule having: (a) a domain, or set of conditions to be satisfied by inputs, (b) a range, or set of anticipatory conditions characteristic of the outputs the knower expects the rule to produce, and (c) an operation or procedure (algorithm) which, when applied to inputs in the domain, generates a unique output (e.g., Scandura, 1970b).

My students and I used rules, so defined, during the 1960's in the analysis and empirical study of a wide variety of rule-based phenomena, ranging from simple to complex. (Many of these studies are summarized in Scandura, 1969, 1976.) This characterization was subsequently adopted in research by a number of influential educational psychologists (e.g., Merrill, P. F., 1978; Merrill, M. D. and Boutwell, 1973; Schmid and Gerlach, personal communication) and apparently is now widely accepted.†

OVERVIEW OF THE STRUCTURAL LEARNING THEORY

The Structural Learning Theory 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 the Structural Learning Theory defines a class of theories much as is the case, for example, with the Stimulus Sampling Theory of S-R behaviorism (e.g., Estes, 1959).

The Structural Learning Theory, however, is not simply a scientific language. As we shall see below, 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., Scandura, 1977b: Scandura and Scandura, 1978).

As shown in Figure 1, the theory is concerned with: (a) the specification

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†Since its early development, this characterization has undergone a number of important refinements. For example, although rules are similar to "productions," as originally conceived by the logician Post (see Minsky, 1967) and later utilized for psychological purposes by Newell and Simon (1972) and other members of the Carnegie school, they are not identical. Specifically, the operations/procedures in rules, although restricted as to form, are more general than those in productions. Also, productions do not distinguish ranges apart from what one gets when an operation is applied. Both differences, while seemingly technical, are crucial in converting the rule construct into an operational scientific theory that is sufficiently broad to encompass the instructional process.

The earliest systematic presentation of the theory (Scandura, 1971a), although somewhat outdated, still provides perhaps the best introduction although Scandura (1977c) provides a useful survey. The first volume on structural learning (Scandura, 1973) provides a relatively formal treatment but the more recent book on problem solving (Scandura, 1977b) provides perhaps the clearest version along with important refinements, extensions, and applications to education. The most recent book, edited by Scandura and Brainerd (1978), and the Journal of Structural Learning (volume 6, no. 4) include instructive Commentaries on Problem Solving.
WHAT MUST BE LEARNED

In the theory, "content" is effectively characterized in terms of the tasks, or problem situations, that the teacher wants the learner to master (or to deal with effectively), and is referred to as a problem domain.* The prototypic processes that collectively make it possible to solve problems in a problem domain are referred to as rules of competence. (Rules of competence are defined as indicated above.) 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."†

It is important here not to confuse “problem domain” with sets of "behavioral objectives.” While the latter may constitute a problem domain, the converse is not necessarily true. As observed in an earlier exposition (Scandura, 1971c, pp. 28–29), the behavioral objectives approach has a major disadvantage.

“Because the (solution) rules (for each objective) are discrete, they cannot account for behaviors which go beyond the given corpus (i.e., for tasks not associated with one of the given behavioral objectives). . . . For example, suppose (a set of behavioral objectives in arithmetic) only involved rules for adding, subtracting, multiplying, and dividing. In this case, the subject would be unable to even generate the addition fact corresponding to a given subtraction fact, although one might reasonably expect this type of behavior from a person . . . well versed in arithmetic. One might counter, of course, that it would be a simple matter to add a new rule to the original list. (Such a rule might map 5 – 3 = 2 into 2 + 3 = 5, for example.) In effect, when confronted with the criticism that their objectives do not constitute a . . . viable curriculum, (curriculum constructors) would simply say we can add more objectives.

“...This sort of argument ... misses the point entirely. Not only would such an approach be ad hoc—which really says nothing in itself except to convey some ill-defined dissatisfaction—but it would be completely infeasible where one is striving for completeness. To see this, it is sufficient to note that a new rule would have to be introduced for every conceivable interrelationship, and that the number of such interrelationships is indefinitely large. One could easily envision a

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*In structural learning theories, problems are formally characterized (represented) in terms of finite sets of elements, relations and operations defined on the elements, and higher-order relations and operations. (Unlike standard mathematical systems, the relations and operations need not be defined on the same domains and ranges.)
†Note: What is referred to here as "content" corresponds to what others sometimes call educational goals.
number of rules so large that no human being could possibly learn all of them. The sum total of all mathematical knowledge, for example, is so vast that no one has or could possibly acquire all of it. As vast as this knowledge is, however, a really good mathematician is capable of generating any amount of new mathematics which does not appear in print anywhere. That is, he can create. Much of the new mathematics might be utterly trivial, of course, but the very fact that it exists at all strongly suggests that any (behavioral objectives) characterization would almost certainly miss much that is important.

In the theory, then, the term "problem domain" is used in a broad sense, and, in principle, may encompass anything from arithmetic to language or moral behavior. Orthogonally, problem domains may be narrow in scope (e.g., two digit subtraction problems) or comprehensive (e.g., an elementary school mathematics curriculum).

A central problem in all scientifically viable cognitive theories is that of how to represent competence and the Structural Learning Theory is no exception (Scandura, 1971a, 1973). A variety of constructs have been proposed for this purpose, ranging from relational networks (e.g., Quillian, 1968) and frames (e.g., Minsky, 1975), which tend to emphasize static considerations, to productions (e.g., Newell and Simon, 1972) and procedures (e.g., Minsky and Papert, 1972), which emphasize cognitive operations.

Rules (e.g., Scandura, 1970b) fall in the latter category. More specifically, it is assumed in the Structural Learning Theory that the competence underlying any given problem domain can be represented in terms of finite sets of rules (e.g., Scandura, 1971c), each of which may be represented in terms of elementary or atomic components (e.g., Scandura, 1970b, 1976).

Theoretically speaking, the problems associated with any given problem domain can be solved in any number of ways (e.g., via any number of rule sets). In practice, however, only a small number of alternatives normally will be compatible with how a teacher wants her students to go about solving them. It would make a big difference, for example, whether the teacher simply wants her students to be able to perform successfully on a given class of tasks (e.g., subtraction problems) or whether she also wants the students to do so with "understanding" (e.g., to be able to relate the process to concrete reality). The underlying rules of competence necessarily reflect these preferences. In a similar vein, for example, German children are taught the equal additions method of subtraction, whereas American children are taught borrowing. (Note: In the unrestricted Structural Learning Theory (i.e. not limited to instruction), rules of competence are more generally viewed as prototypic of some subject population—for example, prototypic of how concrete operational children are assumed to solve conservation tasks. Scandura and Scandura, 1978.)

Whereas teacher expectations place constraints on the form of what is to be learned, the entering capabilities of the student population determine the level of detail with which competence rules must be specified. Thus, for example, whereas reading may be assumed to be an elementary or atomic operation for most college students, this certainly is not true of third graders. In general, 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 capabilities is not a practical limitation, even in principle. Not only have psychologists long made such assumptions implicitly, but it is always possible to reduce sufficiently the amount assumed so that the capabilities of students in the target population are not exceeded. In effect, assumed encoding and/or decoding processes can always be detailed in terms of (internal) rules, together with simpler forms of encoding or decoding. Given a problem like

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for example, it is normally assumed that all students will encode the digits in the standard way. While such an assumption might be quite realistic with most second graders, this is not necessarily the case with children who cannot yet read or write. In the latter case, for example, the assumed decoding capabilities could be reduced by absorbing into the rules the processes by which simple line segments, curves, and corners are combined to form the digits. (Correspondingly, notice that one could analyze the writing process in this way.)

2) By assuming minimal encoding/decoding capabilities in this way, it is possible to make unambiguous inferences concerning cognitive processes; the rules (and certain cognitive universals mentioned below) contain all that is important so far as explaining, predicting, and controlling behavior with respect to the given problem domain is concerned.
atomic in the sense that they are relatively simple that the students in question cannot master part of such a component without mastering it all. (Basic mathematical considerations guarantee some such level of representation, Scandura, 1970a, 1976; Suppes, 1969.)

In solving problems (i.e., in generating outputs associated with given inputs), it is not necessary that this be accomplished directly by applying "higher-order" rules individually. Rather, in the Structural Learning Theory solutions may be generated indirectly since rules are allowed to operate in higher-order fashion on other rules (see previous footnote) to generate new rules. The new rules, in turn, may generate the solutions.

"Higher-order rule," as the term is used here, should not be confused with other common uses of the term, most especially with rules that are associated with higher levels in learning hierarchies (cf. Gagne, 1970 and Ehrenpreis and Scandura, 1974). Whereas the latter (e.g., Gagne, 1970) involve combinations of lower-order rules, our higher-order rules include, for example, the processes by which lower-order rules, associated with any number of different hierarchies, are combined to form correspondingly more complex rules (i.e., "higher-order rules" in Gagne's terminology).

This is not to say that the only thing higher-order rules are good for is to combine lower-order rules in learning hierarchies. A wide variety of behavioral phenomena can be accounted for in this way: learning (rule derivation/"invention"), breaking problems into sub-problems (including constructing hierarchies of sub-problems), assigning meanings, motivation or rule selection, problem definition, storage and/or retrieval from memory, automatization, etc. (e.g., see Scandura, 1977b, 1978). The basic differences in each case reside in the general types of higher-order rules required. "Invention," for example, may involve higher-order analogy rules, which construct new rules having the same form as given ones, as well as higher-order composition rules, which serve to integrate component rules into more comprehensive wholes.

The explicit introduction of higher-order rules has a number of important general advantages: (1) Higher-order rules represent interrelationships in a way that appears to allow for "creative potential" (i.e., unanticipated outcome). In addition, the introduction of higher-order rules, as well as lower-order ones, often makes it possible to account for relatively complex domains in an unusually efficient manner (e.g., Scandura and Durning, 1977). (2) As indicated in the section on The Learner, higher-order rules (along with lower-order rules) appear to provide a general and viable means for representing individual knowledge (i.e., actual human behavior potential). Moreover, their introduction for this purpose is highly consistent with what is known (or at least what may safely be assumed) about how humans function as information processors. (3) As we shall see in discussing individual differences measurement, higher-order rules, just as rules in general, are fully operational. It is possible by testing to determine which part of which higher-order rules have and have not been acquired by individual learners at any given stage of learning. (4) Finally, the introduction of higher-order rules appears to facilitate the relatively difficult task of specifying the competence underlying complex problem domains. The quasi-systematic form of analysis that has been used for this purpose is called structural analysis.

THE PROCESS OF STRUCTURAL ANALYSIS

Detailed structural analyses have been undertaken of several rather comprehensive problem domains, including geometry construction problems (Scandura, Durning, and Wulfeck, 1974), an entire mathematics curriculum for elementary school teachers (Scandura et al., 1971), algebra proofs (Scandura and Durning, 1977), arithmetical skills (Scandura, 1972), and, most recently, the domain of Piagetian conservation problems (Scandura and Scandura, 1980). Empirical evaluations strongly supportive of the analyses involving geometry construction problems (Scandura, Durning, Wulfeck and Ehrenpreis, 1977), the mathematics curriculum (Ehrenpreis and Scandura, 1974), arithmetical skills (Scandura, 1972), and conservation (Scandura and Scandura, 1980) have been completed.

The point to emphasize here, perhaps, is that the constraints imposed on the representation of competence in structural learning theories go beyond those normally associated with a scientific language. As we shall see, these constraints play an important role in satisfying the needs of instructional theory. Specifically, unlike most cognitive theorizing, considerable attention has been given to the crucially important problem of how to identify the rules of competence underlying given problem domains. In the case of instruction, for example, it is one thing for a teacher to be able to give examples of the kinds of problems she wants her students to solve or to illustrate the kinds of things that must be learned; it is quite something else to be able to identify precisely and comprehensively what it is that her students need to learn in order to solve all or most of the problems. Clearly, being able to represent needed competence involves much more than simply being able to solve problems by oneself or agreeing on some form of representation.

In general, structural analysis involves: (a) specification of the problem domain, including both the individual problems and the extent of the domain and (b) specification of the rules needed to solve the problems. In
In the case of relatively simple domains, for example the domain of subtraction problems, both the problems and the underlying solution rules can be specified relatively easily.

Sample subtraction problems and a subtraction rule (algorithm) based on "borrowing" is shown in Figure 2. In addition to mastery of the content, the major prerequisites for reliable analysis in simple cases such as this one would appear to be (a) some facility in constructing flow diagrams and (b) representing them at a level of detail (i.e., in terms of atomic components) that is appropriate for the students in question.

The situation with more complex domains is far less obvious. For one thing, it is not always easy to identify the effectively operating problems, or the extent of the given problem domain. Both factors, for example, had to be dealt with in our recent analysis of the Piagetian stage of concrete operations (Scandura and Scandura, 1980). As presently practised, the constraints on structural analysis in this regard reside primarily: (a) in the required form of representation (e.g., of problems as a type of structure) and (b) in the need for, if not an analytic description of the domain, then the existence of some oracle (e.g., teacher) who, given an arbitrary problem, can determine whether or not it belongs to the domain.

Considerably more work has been done in identifying the rules of competence underlying complex domains. Specifically, in addition to rules of competence per se, progress has been made toward the development of systematic and relatively efficient methods of structural analysis (designed to identify rules of competence).

Unlike simple domains, complex domains are not easily reduced to single rules of competence: Some domains may not be thus reduced, in principle as well as in practice. To some extent, this difficulty is circumvented in structural analysis by adopting a modular approach.

In schematic form, structural analysis begins with some given domain of problems and involves the following steps: (1) Select a representative sample of problems. (2) Identify a solution rule for solving each of the sample tasks. (These solution rules are designed to reflect the way in which successful subjects in a given target population might solve the sample problems; the initial set of solution rules is denoted $R_0$). (3) Identify higher-order rules which reflect parallels among the initial solution rules and which operate on lower-order rules. (4) Eliminate lower-order rules made unnecessary by the higher-order rules. (5) Test and refine the resulting rule set on new problems from the problem domain. (6) Extend the rule set where necessary so that it accounts for both familiar and novel problems in the domain. Collectively, the higher- and lower-order rules of step (3) constitute a more basic set of rules from which the initial solution rules, among others, may be derived.

In recent work, we have discovered what appears to be a close relationship between devising prototypic solution rules and "top-down" programming, a general method often used in computer programming to construct what are called "structured programs" (See Haskell, 1978, for a highly readable introduction.) Use of this method to supplement existing forms of structural analysis appears to have considerable promise and could lead to the development of reliable, systematic, and efficient methods of analysis. Research in this direction is currently underway.

See previous footnote.
Consider, for example, step (1), two sample problems from the domain of geometry construction problems, and step (2), their corresponding solution rules.

**Sample problem 1**

Using only a straight-edge and compass, construct a point X at a given distance d from two given points A and B.

![Diagram of Sample problem 1](image)

**Solution rule 1**

[Set (the radius of) the compass to distance d, put the point of the compass on point A, and draw a circular arc (i.e., the “locus” of points at distance d from A)]; [place the compass on point B and draw another circular arc]; [label the point(s) of intersection of the two circles X].

**Sample problem 2**

Given a point A, a line l and a distance d, construct a circle with radius d which goes through point A and is tangent to line l.

![Diagram of Sample problem 2](image)

**Solution rule 2**

[Construct a circle with center at A and radius d]; [construct a locus of points at distance d from line l (i.e., parallel line at distance d from line l)]; [construct a circle with center X (the intersection of the circle and the parallel line) and radius d].

Step (3): Notice that the two solution rules have the same general structure [set off brackets]. Although the component rules of these solution rules differ substantially, each solution rule involves two independent “locus” constructions, with the intersection X of the two-loci playing a critical role. In the first problem, X is the solution. In the second problem, it is the center of the desired goal circle.

In general, each type of structural parallel can be realized concretely in the form of higher-order rules. (The above type of parallel is only one of several basic kinds that may be shared by two or more rules.) In the present illustration, for example, both solution rules can be derived by applying the higher-order “two-locus” rule of Figure 3 to the respective component rules. This higher-order two-locus rule operates on simple locus rules (e.g., for constructing circular arcs and parallel lines) and generates solution rules (i.e., combinations of the simpler locus rules). It is important to emphasize, that the two-locus higher-order rule can be used to derive solution rules for a wide (potentially infinite) range of problems not just for the two sampled problems.

(Incidentally, notice also that the higher-order rule is only represented schematically. For example, the notion of a “locus condition” in the first decision would almost certainly not be atomic (i.e., sufficiently elementary) with respect to most populations of learners. For this purpose, “locus condition” must be detailed in terms of the more basic conditions shown in Figure 4—such as the “picture” contains a point X that is a given distance from two given points or lines or is equidistant from two pairs of given points or lines.)

Step (4): Given the higher-order two-locus rule and the lower-order component rules, the solution rules themselves may be eliminated as redundant since they can be derived from the former rules acting collectively. Illustrating steps (5) and (6) of structural analysis would require more space than is available, but the general intent is clear. For details of the analysis, see Scandura, Durnin and Wulfeck (1974).

It is important to notice that structural analysis may be applied iteratively (i.e., repeatedly). Given an initial set of solution rules, one need not stop by deriving a more basic rule set (e.g., a set including both higher- and lower-order rules). The derived rule set, in turn, can be subjected to precisely the same type of analysis with the result being a rule set that is still more basic. In general, structural analysis may be reapplied.

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†Each step in Solution Rule 2 can be detailed in terms of the more molecular operations of setting a compass, using a fixed compass to construct a circular arc, and using a straight edge to construct a line segment.
as many times as desired, each time yielding a rule set that is more basic in two senses: (a) individual rules are simpler and (b) the new rule set as a whole has greater generating power (i.e., it provides a basis for solving a greater variety of tasks, see Scandura, 1973, pp. 114–117; 1977b).
was trained on 304 discrete solution rules. The other (H) was trained on the reduced set of 164 solution rules plus 5 higher-order rules. The results showed: (a) All of the students learned the solution rules that they had been taught to a high degree of proficiency. (b) Those H subjects who were trained on the higher-order rules performed just as well on transfer tasks requiring new solution rules (which they had to derive) as did those D subjects who were trained on the solution rules directly. (c) The higher-order rules (H) group performed better on transfer tasks on which neither group had been trained. The results, without serious distortion, can be summarized by saying that "the higher-order rules students were taught less but learned more."

In another project, Scandura, Durnin and Wulfeck (1974) undertook a more intensive analysis of geometry (straight-edge and compass) construction tasks. Among other things, this study demonstrates that the heuristics identified by Polya (1962) can be sufficiently detailed that children can be taught to use them both successfully and reliably. (Also, they were programmed on a computer.)

A subsequent empirical analysis (Scandura, Wulfeck, Durnin and Ehrenpreis, 1977) demonstrated that the identified 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 cited above. Specifically, the predictions referred to individual performance on specific problems rather than to group averages.

Nonetheless, the analytical results of the Scandura et al. (1974) study were limited in a number of important ways: (a) No attempt was made to include logical inference. (b) All of the higher-order rules had the effect of composing rules—no other kinds of higher-order rules were considered. (c) No distinctions were made between deriving solution rules and breaking problems into subproblems. The analysis did not, for example, allow for the widely used technique of breaking problems into hierarchies of subproblems and attacking the subproblems in turn.

A subsequent study by Scandura and Durnin (1977) dealt specifically with these limitations. In particular, a total of 24 lower-order and higher-order derivation and problem definition rules were shown to be adequate for proving all 130+ theorems and proof exercises (along with an undetermined number of others) in an experimental high school text on number systems (Brumfield, Eicholz and Shanks, 1961). In addition to dealing directly with logical inference, the higher-order rules identified in this study involved analogy, generalization, restriction, and subproblems, as well as simply combining lower-order component rules. Another study (Lowerre and Scandura, 1973) dealt with logical inference in the context of verbal discourse. In this case, it was possible to both identify and teach rules dealing with logical interrelationships among sentences.

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. At first we were puzzled as to why this had not been a problem in the other analyses. It later occurred that there was a very good reason. Unlike the earlier analysis of my mathematics text, and the subsequent analysis of the Brumfield et al. Algebra text, the geometry problems were not organized in the form of a curriculum. Rather, the problems were randomly selected from Chapter 1 of Polya's (1962) mathematical discovery. The problems, in effect, were not ordered according to ease of learning but rather to make the points Polyja felt essential to his discussion of heuristics.

This recognition opened up to us a whole new area of concern, fortunately one that could be dealt with in a surprisingly simple way. As noted above, once one has identified a set of lower- and higher-order rules underlying a problem domain (more accurately a set of rules derived from a finite sample of problems taken from the domain), there is nothing to prevent one from repeating the analysis. Thus, by seeking out relations and parallels among lower- and higher-order rules identified on the first go-round, one can frequently identify a second generation of higher- and lower-order rules from which the original ones may be derived.

In fact, this is precisely what Wulfeck and Scandura (1977) did in extending the geometry analysis of Scandura et al. (1974). Structural analysis was repeated iteratively until all of the rules, higher- and lower-order alike, consisted of such molecular operations as setting a compass, using a fixed compass to construct a circular arc, and combining pairs of simple operations. Not only were the individual rules simpler but, collectively, they had qualitatively more generating power.

Moreover, introducing limitations on processing capacity (see discussion below on The Learner) made it possible to generate optimal learning sequences (i.e., to sequence any given set of problems in a learnable order). Comparison of these theoretically derived sequences with learner-controlled and random varieties indicated an approximately two-to-one advantage in favor of the former. This difference held even though remedial training was provided on needed solution rules immediately after a subject failed a problem, thereby helping to insure that the controls would not get further and further behind. Success on problems that came later in the instructional sequence, however, required new and more complex higher-order rules as well as new solution rules. According to
the theory, learners would gradually acquire the needed higher-order (as well as lower-order) rules as learning progressed. Hence, it appears that the obtained difference was due to the fact that the experimental subjects (and others who succeeded in solving the problems by themselves) gradually learned the needed higher-order rules whereas the unsuccessful controls did not.

Scardua and Scardua (1980) further demonstrated the applicability of structural analysis to what are normally thought of as “unstructured” domains; specifically, they systematically analyzed the domain of Piagetian conservation tasks. Beginning with a rule-based characterization of the prototypic concrete operational child, successive reapplication of the method of analysis resulted in the identification of increasingly more primitive sets of rules—leading ultimately to rules characteristic of the preoperational child. The identification of preautomatized versions of the rules used by conservers played a key role in the analysis. In effect, the structural analysis not only provided a (partial) characterization of competence at two different stages of cognitive development but also of the transition between them. This analysis, in turn, provided an explicit basis for training preoperational children to conserve in a manner that was difficult to distinguish from that of natural conservers. Perhaps more important, it was possible to explicitly manipulate “horizontal decalage” (i.e., uneven transfer across conservation concepts), something which has been difficult to explain, let alone to predict or control within Piagetian Theory.†

THE LEARNER

Prototypic competence is not the same as rules of knowledge which characterize individual behavior potential. It is assumed in the Structural Learning Theory that what an individual does and can learn depends directly and inextricably on what he already knows. More particularly, as shown in Figure 1, it is assumed that human cognition may be adequately characterized in terms of: (a) universal characteristics of the human information processor and (b) individual knowledge. As we shall see, the latter is operationally defined in terms of rules (of both higher- and lower-order) relative to prototypic competence (prototypic competence being associated with given problem domains and learner populations).

†Fein (1978) made similar use of the Structural Learning Theory in designing a comparative training study involving formal operations. Essentially, what he found was that explicit rule-based training leads to more rapid growth than does less directive incongruity training. The results of the study further demonstrate the need for more detailed and operational analysis of formal operations along the lines indicated above.

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 that are inherent to man generally; they need not, and indeed, in some cases cannot be taught.

UNIVERSAL CHARACTERISTICS OF HUMAN COGNITION

Control mechanism

Control mechanisms are among the most important universal characteristics. They are essential in all information processing systems, whether man or machine, and serve to tell the learner which rules to use and when to use them. Whereas all complete information processing theories make a distinction between processes (rules) and control, control in most cases either plays a subordinate role (e.g., Newell and Simon, 1972), or is distributed among a variety of different control mechanisms whose coordination, in turn, is often left unspecified (e.g., Pascual-Leone, 1970).†

†Equally important, the amount of information processing that is designated as control and the amount that is designated as process is largely arbitrary. As with encoding/decoding and internal processing, the decision as to how much of a theory to assign to control and how much to other internal processes (e.g., rules) depends on factors other than simply accounting for a specific domain of behavioral phenomena.

In the Structural Learning Theory, a primary consideration has been to insulate that (rule) constructs reflecting individual knowledge are operational (i.e., definable in terms of observable behavior). Furthermore, I wanted the division between control and other internal processes to be generalizable, and if possible to be completely independent of specific content and subject populations. Put differently, I did not want to assign more to control than could reasonably be assumed of all human processors. If one were to assume too much, then there surely would be some populations of subjects who would be unable to perform as expected—even where they had mastered all of the requisite internal processes (e.g., rules and higher-order rules). On the other hand, I wanted to assume as much as possible. Doing so simplifies the identification of competence associated with specific content.

I cannot prove in any formal sense that the division of labor (between control and rules) proposed in the Structural Learning Theory is the only one that would satisfy the above considerations. This division, however, does appear to meet these constraints more completely and precisely than any other cognitive theory with which I am familiar (or for that matter with any other alternatives that I have been able to devise). Indeed, many well-known cognitive theories appear not to have even attended to these considerations; in some cases, as mentioned in the main text, they have been demonstrated empirically to be in error.

Thus, for example, although our research demonstrates that all rules, including higher-order rules, are teachable, it also demonstrates that one may not safely assume the uniform availability of even the simplest higher-order rules, as is frequently the case in other comprehensive cognitive theories. In the General Problem Solver (e.g., Ernst and Newell, 1969), for example, it is assumed that means-ends analysis is characteristic of all problem
In contrast, in structural learning theories control mechanisms have been subjected to direct empirical study (e.g., Scandura, 1971a, 1973, 1974, 1977b). It is well known, for example, that people are not always able to solve problems, even where they know all the necessary components. What has not been so clear, however, is why this is so. Are successful persons somehow more capable than the others? Or, do they simply know something that unsuccessful people do not?

The explicit introduction of higher-order rules helps provide answers to these and a wide variety of other questions. As observed above, for example, higher-order rules may provide an explicit basis for explaining, predicting and/or controlling behavior involving analogy, generalization, problem definition, rule selection, etc. (For details, see Scandura, 1973, 1977b).

As noted above, however, even introducing higher-order rules does not provide a sufficient basis for explaining individual behavior. A complete theory must include (control) mechanisms which explain how and why various rules are used in particular situations. In this regard, the Structural Learning Theory postulates a simple goal switching control mechanism that makes minimal assumptions about the processor, assumptions that appear to be generalizable to all people. This mechanism simply makes precise what has been implicitly assumed for many years. If a person does not know how to solve a given problem, but still wants to solve it, then he will automatically turn his attention to finding some way to do it.

More specifically, given a problem the human information processor is assumed to first check to see if a solution is directly available. If not, the processor is assumed to search through (the ranges of) his available rules to see which, if any, might solve the problem. (A rule is a potential solution rule if its range “matches” the problem goal and its domain includes the problem given.) If a unique rule is found, then the rule is applied and the output is tested to see if it solves the problem. If there are no potential solution rules, then the search takes place at a still deeper level. In this case, control directs the search for (higher-order) rules that generate potential solution rules.

If such a higher order rule is found, then it is applied; the newly generated rule is added to the set of available rules and the search reverts to the next lower level. The augmented rule set is then checked as before; only this time the newly derived (potential) solution rule is available. In

general, whenever there are no rules (or more than one rule) which apply at a given level of search, control moves to a still deeper level. Conversely, whenever a match is achieved (so that a rule is applied), control reverts to the preceding level.

This simple “goal switching” mechanism is hypothesized to be common to all humans and to govern all cognition, irrespective of the specific knowledge involved. Consider, for example, the problem of rule derivation, of how individuals derive new solution rules for solving new problems they have never seen before. According to the Structural Learning Theory, rule derivation takes place as a result of applying various higher-order rules to other rules. These higher-order rules may serve to combine component rules, to generate analogous rules, to generalize given rules, etc.

To make things concrete, suppose a child knows rules for converting yards into feet (multiply by three) and for converting feet into inches (multiply by twelve) and that he is asked “How many inches are there in two yards?” Clearly, this problem can be solved by combining the two available rules, the rule for converting yards into feet and the rule for converting feet into inches. But how does the child know how to combine the given rules? Knowing component rules is surely not logically equivalent to knowing when and how to use them.

A basic assumption in the Structural Learning Theory is that new rules are derived by application of certain rules to other rules. In the present case, a child might be expected to succeed if he knows a higher-order rule that operates on pairs of rules of the form, A→B, B→C (i.e., like but not limited to those above), and combines them to form composite rules of the form, A→B→C, in which the components are performed in sequence.

While knowing both requisite higher-order rules and requisite lower-order rules is a necessary condition for solving problems this is not sufficient. In order to effectively use available rules to derive solution rules and to solve problems, some type of control mechanism is needed to

In earlier formulations (e.g., Scandura, 1971a, 1973, 1977b), emphasis was given to switching between higher- and lower-level goals and, correspondingly, the control mechanism referred to as the “goal switching mechanism.” The above description is behaviorally equivalent to these earlier formulations. However, although it is beyond the scope of this article to discuss the reasons, recent theoretical advances and computer implementations of the mechanism convince me that the formulation sketched above is preferable. Among other things, it makes it possible to program the control mechanism in a way that is completely independent of content (i.e., specific rules of competence). The latter can be removed, replaced, and/or modified without requiring any change in control. Strictly speaking, implementation of the goal-switching mechanism, as originally conceived, is not possible. In this case, it is necessary either to restrict oneself to incomplete approximations (e.g., Wulfek and Scandura, 1977) or to introduce natural but nonetheless ad hoc assumptions concerning specific sets of competence rules.

Solving. Similarly, cyclical stack-type control has been commonly assumed in simulation theories based on production systems (e.g., Newell and Simon, 1972). These types of control, while perhaps common, implicitly make assumptions about how people utilize lower-order knowledge that are not universal.
determine when each rule is to be used and how. The question here is whether the above control mechanism is sufficient for this purpose and, if so, whether this mechanism is available to all human beings as postulated. Although the former question is strictly analytic in nature (and, hence, has an analytic answer e.g., see Scandura, 1977b, Chapter 2), it seems best here to consider both questions in the context of empirical evidence.

Specifically, in a study reported by Scandura (1973, 1974), 30 seven-to-nine year-old children were trained on simple A→B and B→C conversion rules and tested on an A→C problem. In most information processing theories based on production systems (e.g., Newell and Simon, 1972) it is (sometimes implicitly) assumed that people automatically combine rules. If all humans can actually do this, then all of our subjects would be expected to succeed on the problem. The fact that 24 of 30 subjects failed strongly suggests that many people do not automatically combine rules, at least not young children.

With the above control mechanism in mind, the 24 subjects who failed on the A→C problem were randomly divided into two groups of 12. One group was trained on the higher-order composition rule identified above. The other group served as a control. After the higher-order rule training, all subjects were trained on a new pair of A′→B′, B′→C′ rules, which the subjects had never seen before. Then, they were tested on the corresponding A′→C′ problem (which was also new). This time essentially all of the experimental subjects succeeded whereas all of the control subjects again failed.

These results are perfectly in accord with the hypothesized control mechanism. Given the A→C pretest problem, for example, the 24 failure subjects did not have a solution rule immediately available, nor apparently did they know an appropriate higher-order rule. They only knew an A→B rule and a B→C rule (e.g., rules for converting yards into feet and feet into inches). Under these conditions they failed uniformly.

After training on the higher-order composition rule, the experimental subjects fared uniformly well. Presumably, according to the goal-switching control mechanism, the subjects first checked to see if they knew the solution (to the A′→C′ problem). Not finding one, they again searched their available knowledge, this time looking for a rule that generates potential solutions (e.g., numbers of inches) and that applies to the given input (e.g., two yards). Again, no such rules were available. Hence, another search was initiated, at this level for a (higher-order) rule that generates potential solution rules. According to hypothesis, this level of search resulted in the identification of the higher-order composition rule mentioned above. The range of this rule, recall, contains the A′→B′→C′ solution rule. Its domain consists of pairs of rules of the form, X→Y, Y→Z, and, hence, clearly contains the given pair A′→B′, B′→C′. According to hypothesis, the higher-order rule is applied to the A′→B′, B′→C′ rules giving A′→B′→C′. The latter, composite rule is added to the set of available rules (i.e., it is learned) and control reverts to the previous level. The subsequent search again is for a solution rule, only this time the A′→B′→C′ rule is available. Once identified, this rule is applied and the problem is solved. (That is, the potential solution obtained by applying the composite rule is tested to see if it satisfies the original goal.)

I must caution that this simple control mechanism is an idealization and applies only in situations where processing capacity is not a factor, and specifically where all of the requisite higher- and lower-order rules are learned perfectly and are active in “working” memory. (See Scandura, 1971a, 1973, 1977b.) Perhaps surprisingly, however, this limitation has not proved to be as critical as one might expect. Empirical support has been strong, although not deterministic, even under “real-world” conditions. Ehrenpreis and Scandura (1974), for example, found that higher-order (as well as lower-order) rules underlying a college course for teachers could be identified in a systematic manner and that instruction on such rules had a highly positive effect on pre-specified kinds of “far transfer”. Furthermore, the degree of transfer was directly related to the degree to which the test conditions approximated the ideal (Scandura, 1977b, chapter 11).

When used in conjunction with appropriate kinds of higher- and lower-order rules, the goal switching control mechanism provides an adequate basis for explaining, predicting and controlling a wide variety of behavior. These include: solving analogy problems, generalizing given rules, motivation (rule selection), problem definition (sub-goal formation), automatization, and rule retrieval. For details and related empirical support the interested reader is referred to Scandura (1973, 1977b).

PROCESSING CAPACITY AND PROCESSING SPEED

Processing capacity is the second general characteristic of the theory that has been empirically tested (e.g., Scandura, 1973; Voorhies and Scandura, 1977). In one form or another, almost all contemporary information processing theories assume that “working memory” has a limited capacity. In contrast to most theories, however, working memory in the Structural Learning Theory is assumed to hold not only data (the stuff on which rules operate) but rules (processes) themselves. 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 attacking 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 (e.g., see Scandura, 1973, Chapter 10).
Thus, for example, whereas it may be impossible to multiply large numbers in one's head using the standard algorithm, many people know short-cut processes that enable them to perform successfully. Rather than applying to all multiplication problems, short-cut processes typically work only with special types (e.g., numerals ending in 5 or 0).

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 nature of the response itself, the underlying rules must be represented in more detail (than in the latter case). 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 require equal processing times. (Rules that are represented in terms of such components are called "process atomic", Scandura, 1977b, pp. 111–135. In contrast, predicting responses per se requires only that rules be represented in terms of behaviorally atomic components.)

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 sub-classes of structural learning theories are readily distinguished. In one sub-class, the theories involve only the control mechanism and rules represented in terms of behaviorally atomic components. Theories of this class make it possible to predict individual responses but they are silent on the issue of processing time. As noted above, these are idealizations that fit reality only to the extent that processing capacity is not a factor. Thus, deterministic predictions may be expected to hold only in situations that satisfy appropriate boundary conditions. To the extent that processing capacity is involved, for example, theoretical predictions may be expected to deviate from obtained results.

In many ways, such theories may be likened to theories in classical physics. The inclined plane law, for example, allows one to calculate the force needed to move a given cart up an inclined plane but only where the inclined plane is perfectly smooth and the wheels on the cart are frictionless. Deviations from prediction may be expected just to the extent that the inclined plane is bumpy and/or that friction otherwise plays a role. Correspondingly, structural learning theories can only be tested under appropriate idealized conditions in the same sense that the inclined plane law must be tested using smooth inclined planes and frictionless wheels.

The second sub-class of structural learning theories involves the control mechanism, processing capacity/speed, and process atomic rules. Theories of this type obviously provide more detailed accounts of behavioral phenomena and can validly be tested under less stringent conditions. For example, the experimenters need not ensure that processing requirements lie within each subject's processing capacity. Encoding/decoding assumptions still must be met, however.

Increasing the range of applicability does not come without a price; theories of the second type are correspondingly more difficult and exacting to construct. Thus, for example, although traditional cognitive psychology is replete with theories that predict latencies, few satisfy the aforementioned structural learning constraints. Among those that appear to come closest are the chronometric theories of simple arithmetic by Groen and his associates (e.g., Suppes and Groen, 1967) and, especially, the list processing and computational theories of Voorhies and Scandura (in Scandura, 1973, 1977b).

ASSESSING INDIVIDUAL KNOWLEDGE

In contrast to universal cognitive constraints, specific knowledge is assumed to vary over individuals. The theory shows how prototypic competence (i.e., competence prototypic of given populations) may be used to operationally define the knowledge available to actual individual members of such populations. Specifically, the theory tells how, through a finite testing procedure, one can identify which parts of to-be-taught rules individual subjects know. The rules in a very real sense serve as rulers of measurement and provide a sufficient basis for the operational definition of human knowledge (see Scandura, 1977b, chapter 2).

Clearly, this is not the place to detail how this may be accomplished in general. For one thing, discussing the way process atomic rules are operationalized gets one deeper into issues of representation than would be desirable here. (For details see Scandura, 1977b.)

For present purposes, it will be sufficient to consider the process of assessing individual behavior potential with respect to rules of competence represented in terms of behaviorally atomic components. Even here, we consider operationalization only with respect to single rules rather than with respect to sets of competence rules considered collectively. The flow diagram in Figure 2 depicts a rule (procedure/algorithm) for subtracting numbers. This rule is broken down into atomic components (i.e., steps that are so simple that each individual in the target population may be assumed able to perform each step either perfectly or not at all). In line with our previous discussion, it is worth emphasizing that what are atomic units relative to one population may not be atomic units with respect to another (e.g., less sophisticated) population.

Because success on any path of a rule depends on success on all atomic components, each path through the rule also acts in atomic fashion.
Furthermore, there are only a finite number of behaviorally distinct paths. We do not distinguish paths according to the number of repetitions of loops, because the same cognitive operations and decisions are required regardless of how many times a given loop is traversed in carrying out a given "cognitive computation".

Collectively, the paths of the subtraction rule impose a partition on the domain of column subtraction problems: That is, they define a set of distinct, exhaustive, and homogeneous equivalence classes of subtraction problems such that each problem in a given equivalence class can be solved via exactly one of the paths.

One path through the aforementioned subtraction algorithm is represented schematically at the bottom of Figure 2, along with two-column subtraction problems to which that path applies. The first node designates START. Operation (arrow) 1 says to go to the right-most column. The second node, then, asks whether the top number is greater than the bottom number. Since the answer is "yes," Operation 2 is applied (i.e., the bottom number is subtracted from the top number). Next (Node 3), we ask if there are any more columns. If there are, we proceed to the next column (Operation 3) and repeat. Otherwise we STOP.

The fact that each path is associated with a unique subclass of column subtraction problems makes it possible to pinpoint through a finite testing procedure exactly what it is that each subject knows relative to the initial rule. It is sufficient for this purpose to test each subject on one randomly selected item from each equivalence class. Success on each item, according to our atomicity assumptions, implies potential success on all other items from the same equivalence class, and conversely for failure.

Individual knowledge (or behavior potential), in effect, may also 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 and fails on the others, 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.

Fortunately, the above discussion is not just a theoretical exercise. A significant amount of supporting data has been collected over the past several years on a variety of problem domains, with subjects ranging from preschool children to Ph.D. candidates. Given a class of tasks, the general form of each study went as follows: (a) 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) These rules singly and/or collectively 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 initial items, to predict performance on new (second) items with over 96% accuracy (Scandura, 1973; Scandura and Durnin, 1978). 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 (Durnin and Scandura, 1973).

There is one further major advantage of the structural approach to assessing behavior potential: The approach makes it possible to identify precisely not only what individuals can and cannot do, but also what the learner does and does not know relative to the particular rules involved. A simple basis for instructional decision making follows directly: Assume the paths the learner already knows and gradually "build in" those that he or she does not.

In summary, it would appear that any viable theory of performance testing must take into account underlying competence. Not only do rules of competence (associated with populations of subjects) provide a basis for measuring individual knowledge and for providing remedial instruction but they also provide an explicit basis for selecting appropriate test items.

In the latter study, the equivalence classes determined via the structural/algorithmic approach were compared with item forms identified by Hively et al. (1968) and by Ferguson (1969). Whereas the levels of prediction on success items were approximately the same, the algorithmic/structural approach yielded significantly better results with respect to failures. Equally important, these levels of prediction were obtained with half as many test items—with even greater increase in efficiency possible through the use of conditional testing (Durnin and Scandura, 1973).

In addition to yielding poorer results, the use of item forms has been limited to paper-and-pencil tests. And as noted by Gagne (unpublished APA invited address, 1971) for example, item forms have intrinsic limitations with regard to non-paper-and-pencil applications such as job analysis. The structural approach is not limited in this way. The direct relationship between molarity of atomic rules and sophistication of population allows for broader applicability. In job analysis, for example, it would make little sense to attempt a molecular analysis of arithmetic skills in order to judge the ability of accountants, or of writing syntax in evaluating professorial capabilities. Although the impatient reader may have some doubts, minimal capabilities can reasonably be assumed of all bona fide professionals. Thus, all trained accountants presumably can add a column of figures, and all experienced Ph.D.s have at least minimal writing capabilities. Hence, it is sufficient to consider only those molar competencies (atomic rules) that distinguish among individuals in the target population—for example the ability to set up and administer efficient accounting systems for companies of various types.
Furthermore, 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).

The interested reader is referred to the literature for information regarding hierarchical relationships among paths and the conditional testing this makes possible (Durnin and Scandura, 1973; Scandura, 1973; Scandura and Durnin, 1978), the consolidation of knowledge (Scandura, 1977b), a possible basis for assessing sentence production capacities (Carroll, 1975), the use of sets of rules for assessment purposes (Scandura, 1977b), and the assessment of skilled performance where response measures (e.g., latencies) more refined than success/failure are required (Scandura, 1973, Ch. 8; 1977b, Ch. 2 and 7).

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, the way they are characterized 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 of instruction that deals with individual behavior in specific situations.

Thus, for example, 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. (The latter issue has already been discussed so only the former is considered here.) Although this is not the place to dwell on technicalities, the procedures in question are restricted to those that can be represented concretely as structured programs (e.g., Haskell, 1978; Alagic and Arbib, 1978). Unrestricted procedures, for example, allow for the generation of new (sub)procedures and their subsequent use in executing such procedures. 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, and moreover, procedures that seem to have little heuristic power or modularity in so far as individual differences measurement is concerned.

At the other extreme, the operations of simple productions (e.g., Post, in Minsky, 1967) are too restrictive. Productions disallow the possibility of internal decisions, for example, and effectively act as atomic rules. The domains and operations, consequently, may not act independently of one another—something that seems at variance with everyday observation. It is quite possible, for example, for a person (e.g., child) to be able to identify any given column addition problem without necessarily knowing how to find its sum.

While the necessary richness might be obtained by introducing (sets of) production systems (e.g., Newell and Simon, 1972) to represent competence, doing so would destroy 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 competence/knowledge, 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 rule procedures (i.e., 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-switching from unrestricted procedures. To summarize, 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 has considerable heuristic power insofar as operationalizing individual knowledge is concerned.

Other features of the rule representation are equally crucial. For example, attaching 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 how and where they can do it. What a person expects a rule to do is not necessarily the same as what the rule actually will do. In tightening a joint, for example, a plumber
might expect (hope?) to stop a leak; instead, he might 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 provides a pragmatically useful basis for identifying what must be learned in instructional situations. Thus, the separation of specific knowledge/competence from control greatly simplifies the task of dealing with high level interrelationships that are frequently involved in 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., what must be learned). I have been equally concerned with the problem of how to identify the competence underlying given problem domains. Clearly, knowing the way in which such competence is to be represented (i.e., the type of representation) is not the same as being able to construct such representations in the first place. As a result of carrying out an increasing number and diversity of research activities, I believe, nonetheless, that it may be possible to construct structural-learning based competence theories in a relatively efficient, systematic and objective manner.† This is especially so in the case of competence theories that are intended to be used for instructional purposes.

Our understanding of how to analyze content has increased dramatically over the past several years; and the future looks even more promising. To see this, one has only to mention the important contributions made by traditional task analysis in this direction (e.g., Gagne, 1962, 1970) and to point out that this method of analysis is a special case of structural analysis.‡ The main advantages of the latter are that it is more precise and that it enables one to analyze more complex domains, where higher order relationships play an important role.

†I am not implying the possibility of automatic theory construction, however. I very much doubt that we will ever have a comprehensive or complete method of analysis. Related questions of possibility and impossibility have been considered in the theory of computation, e.g., Rogers, 1967, but such questions are hard to prove in the context of human behavior because they require making explicit assumptions that one might not be willing to make about (real) people. To my knowledge, the possibility of systematic construction of structural learning theories remains an open question.

‡Although going into the matter here would detract from present concerns, it would be easy to show that other common and pragmatically based methods of analysis, used in instructional planning, also are special cases. The "elaboration" theory proposed by Merrill (1978) provides a case in point. It corresponds directly to starting with the paths a learner knows and progressively adding more elaborate ones.

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 (and evaluated) 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 assessment method proposed, the assumed universals used to (partially) characterize human cognition and instructional methods refer to the entire class of structural learning theories (i.e., to the Structural Learning Theory) 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; Wulfek and Scandura, 1977). There are, however, differences of opinion as to how to achieve these ends.

The field of cognitive psychology, for example, obviously overlaps with structural learning. Nonetheless, contemporary research in the former area rests on assumptions which are quite different than those that have guided developments in structural learning. As we have seen, perhaps most basic is the fact that structural learning has been motivated largely (but not exclusively) by instructional considerations.

In this section, let us consider some of the more basic points of difference between structural learning theories and most contemporary theorizing in cognitive psychology.

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,

†In cognitive psychology generally, heavy emphasis also has been given to such either/or questions as: Is information processed serially or in parallel? Is language (symbolism) necessary for thought? Do people use imagery? For an excellent discussion of such research and its limitations, see Newell (1973). Also see Cohen (1977) for a more comprehensive and even handed discussion of traditional approaches.
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 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 kind of information needed to make instructional decisions concerning individuals.

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 also is 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.

As we have seen, structural learning theories do deal with individual behavior (i.e., the behavior of individual learners in specific situations) but they do so in a generalizable way. In order to achieve this duality, however, it has been necessary to reject both the normative and simulation approaches as inadequate and to adopt a relativistic view of behavioral theorizing. In its essentials, this approach involves: (1) the identification of prototypic competence associated with given bodies of content (tasks) and given target populations (rather than either normative or individual competence) and (2) the empirical evaluation of prototypic competence in terms of its reliability as a base for determining the behavior potential of individuals.

This approach explicitly rejects the implicit assumption of many cognitive psychologists that we can, in fact, find out how people actually do things. This hope, I fear, is forlorn. We can never know exactly the cognitive basis for an individual’s behavior. If we are to avoid the dilemma posed above, the best we can hope to do is to characterize individual knowledge in relativistic terms—relative to predetermined rules of competence. (The latter, in turn, depend on the given problem domain and subject population.)

The precision with which individual knowledge can be specified depends on the extent and detail inherent in the problem domain (i.e., in what is being observed). Beyond a certain point, further discriminations become immaterial and cannot, in any case, be detected within the domain (i.e., with respect to the observables) in question. Thus, for example, competence need not be specified at a fixed level of detail. For some instructional purposes, identified competence might need only to distinguish right answers from wrong. At a deeper level, competence might have to account for degree of skill (e.g., latency) as well.

Similarly, 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 attempts to devise a new solution method. Such possibilities cannot be distinguished within the domain in question; this can only be determined via performance on extra domain tasks—or, equivalently, by redefining the domain of interest.

In addition to our work and that of others consciously working in structural learning, the potential of 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 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

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*Studies which involve intensive observation and/or prediction of behavior as individuals solve problems are methodologically similar.
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 apparent awareness (cf. Siegler, 1978; Wulfeck, 1978).† Second, from our discussion of the Structural Learning Theory (i.e., the class of structural learning theories), 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 representation 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.

In effect, it is not sufficient, especially in so far as instruction is concerned, that competence be represented in terms of some more or less precise information processing language as is commonly assumed in contemporary cognitive theorizing. This lack of attention to broader requirements of instructional systems, I think, is a consequence of the “brick laying” syndrome. One common approach is to start with some scientific language† and to show how it can be used to represent various types of cognitive processes. The important point here is that, if such representation can be effected in one sufficiently rich language, then it also can be accomplished with any number of others. Mathematical sufficiency (generative sufficiency in the case of computational/computer-based theories) does not guarantee behavioral adequacy, especially with respect to instruction.

†During the last couple of years, several related attempts have been made in artificial intelligence to develop more or less comprehensive instructional systems (e.g., Brown and Burton, 1978; Collins, 1978). In addition to instructional theory, however, this work relies heavily on the “brute force” processing capabilities of sophisticated computers. Nonetheless, to the extent that the work incorporates serious theory (apart from pragmatic programming), this theory tends to be highly consistent with the structural learning formulation. This fact is especially apparent in what Brown and Burton call “debugging.”

†All too frequently the language is selected by cognitive theorists on the say-so of computer scientists, whose choice in turn reflects formal mathematical properties unrelated to the needs of behavioral science.

For one thing, assumed constructs in the most commonly used languages are not easily or naturally tied to observables. Thus, for example, relational-network-theories are at best only partially operational (e.g., Cohen, 1977). Typically, one attempts to infer cognitive structure indirectly from latency data. This procedure is imprecise (as well as normative) and is almost totally inadequate for many instructional purposes.

Furthermore, such a procedure typically (although often implicitly) assumes a fixed, static cognitive representation (e.g., a fixed relational net). Otherwise, it would be impractical, if not impossible, to infer structure from behavior (i.e., from a variety of independent measures). The problem is that cognitive structure is not static; it is dynamic and may change at each stage of processing (e.g., Scandura, 1973, 1978).

Moreover, as noted previously, cognitive structure cannot be determined (i.e., defined) independently of process. Rather, structures are best viewed either as assumed internal encodings/decodings or as intermediate states generated and/or operated on by processes (i.e., rules). This raises the question as to why one should attempt to represent static knowledge at all; such knowledge is implicit in the cognitive processes themselves (Scandura, 1973, 1977b, 1978). (As we have seen, the latter (i.e., rules) may be operationally defined in terms of observable behavior.) Reasoning thus brings us full circle back to rules as the basic, operational unit of cognitive functioning.

For another thing, learning and other basic phenomena have posed and continue to pose major problems for other contemporary theories in cognitive psychology—this holds for theories of both the normative and the computer varieties. The way rules have been defined in the Structural Learning Theory, on the other hand, provides a natural, apparently general and precise way to conceptualize the learning process (e.g., Scandura, 1971b, 1973, 1974, 1977b).

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, an important 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. In so far as the evaluation phase is concerned the basic structural learning methodology has been reasonably well established (e.g., Scandura, 1973, 1977b; Durnin and Scandura, 1973; Scandura and Durnin, 1978).

The situation as regards structural analysis (i.e., the identification of prototypic competence) is more open. The feasibility of such analyses has been established in a number of areas (e.g., Scandura, 1977b; Scandura, Durnin and Wulfeck, 1974; Scandura and Durnin, 1977; Scandura and Scandura, 1978) but the method itself is still only partially systematic and objective (e.g., Scandura, 1977b, Chapter 2). More efficient and reliable methods of analysis will be essential to insure its widespread use.†

As noted previously, different methods also are needed for the study of cognitive universals (e.g., Scandura, 1971b, 1973, 1977b). In this regard, Resnick and Gaiser (1976) appear to have followed our lead in their work on the “invention” problem. Among other things, for example, they attempted in their studies to approximate “memory-free” conditions in the 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, of course, 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 is perhaps not fully appreciated, 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 (e.g., Scandura, 1977a, 1977c; Wulfeck and Scandura, 1977). These advances draw heavily on the foundations outlined above.

CONCLUSIONS

Generations of insignificant and/or non replacable research on instruction make it clear that global reference to expository, discovery and other instructional methods will never provide a sufficient basis for instructional

†For some years research in this direction has been carried out in concert with, but largely incidental to, specific structural analyses. As a result of the experience gained from this work, we are now attacking the problem more directly and in a way that may generalize over diverse bodies of content. Progress has been relatively rapid during the past year and I expect that before long we will be in a position to report on our work in the literature.
decision-making (e.g., see Scandura, 1962, 1964). Attempts to “match”
global instructional methods with generalized learner capabilities appear
to have met the same fate (e.g., Cronbach and Snow, 1977). It is now
widely agreed that reliable decision making in the instructional arena will
require direct reference to underlying cognitive operations (e.g., 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 viable theory—a form that conforms to
the Structural Learning Theory (or, equivalently, 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 a 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 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,
as it stands, is neutral with regard 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.†

†There is an equally important matter that has not been given nearly the space it warrants
in the present article: As described, the Structural Learning Theory is restricted to tutorial
situations and does not accommodate unrestricted conversations between two or more
participants. A theory which accomplishes the latter goal has recently been proposed by

Pask (1976). This theory treats phenomena at a rather holistic level, however, and does not
make direct contact with the sort of phenomena treated in cognitive psychology. A challenge
for the future will be to see if the Structural Learning Theory can be extended to encompass
unrestricted conversations while retaining its operational character and degree of specificity
(e.g., see Pask, in press).

†As noted above, I am also concerned (for somewhat different reasons) about the
methodologies commonly used in computer simulation studies (e.g., see Scandura, 1977b,
1978).

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THEORETICAL FOUNDATIONS OF INSTRUCTION


