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Structural (Cognitive Task) Analysis: A Method for Analyzing Content *

PART I: BACKGROUND AND EMPIRICAL RESEARCH

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Having decided on the topic to be taught, the first step in designing effective instruction is to specify precisely what the student is to learn and in what order. In the former regard, behavioral objectives are the most commonly used means for identifying what is to be learned. In comparison to course outlines and general lesson plans, behavioral objectives have the distinct advantage of being operationally precise. It is relatively easy to measure whether or not students have mastered the required material.

Nonetheless, behavioral objectives have two major disadvantages (e.g., Scandura, 1971; Ehrenpreis & Scandura, 1974). First, while behavioral objectives specify what the learner is to be able to do after instruction, they leave open the question of exactly what processes must be learned in order to do that. This is an important intrinsic limitation because it can be proven (e.g., in computer science) that if there is even one process for performing successfully on a class of tasks, then there must be an infinite number of other processes for doing the same thing. As a concrete illustration consider the different possible paths one might follow in moving from location to location. From an instructional perspective, of course, not all of these different processes may be equally desirable or feasible. The second major disadvantage of behavioral objectives is that they do not allow the instructional designer to make provision for the unexpected, in the sense of building into a curriculum the potential for solving unanticipated kinds of tasks. Since the sheer bulk of what might be taught is so vast, it is impossible to teach directly everything that one might need to know. Indeed, our whole educational system is based implicitly on the assumption that learners can evidence some degree of creativity.

The technique used most commonly by designers to sequence instruction is based on task analysis. As with behavioral objectives, traditional task analysis has the major advantage of being relatively easy to apply. Its essentials are well summarized by (repeatedly asking and answering) the familiar question, "What would a learner have to be able to do in order to perform that task?"
As with behavioral objectives, however, traditional task analysis has several major disadvantages. First of all, as typically used, task analysis is relatively ambiguous and imprecise. Two different analysts might start with the same basic class of tasks and come up with quite different analyses, even incompatible analyses. Second, no matter how complex the class of tasks being considered, task analysis treats that class as a whole. The result can be highly complex hierarchies of to-be-acquired skills. Because the skills are so highly interrelated, learning any one skill, in general, may be dependent on learning large numbers of other skills. Finally, traditional task analysis, like the use of behavioral objectives, refers to behaviors to be acquired, and not to what must be learned in order to perform as desired.

Largely as a result of this last mentioned limitation, many instructional researchers have shifted their attention during the last few years toward what has been called "cognitive task analysis" (e.g., P. F. Merrill, 1978; Resnick, 1976; Scandura, 1968, 1971). My colleagues and I have introduced a particular type of cognitive task analysis called "Structural Analysis". This method of analysis, having its roots in our behavioral/analytical research during the 1960's (e.g., Scandura, 1962, 1964, 1969), has evolved more or less continuously during the 1970's.

Structural analysis has several major characteristics which distinguish it either in whole or in part from other types. First, and perhaps most distinctively, structural analysis is firmly grounded in operational theory. It is an integral part of the Structural Learning Theory (e.g., Scandura, 1971, 1973, 1977, 1980). Second, the method is general in that it allows one to deal with arbitrarily complex domains in a strictly modular fashion. As we shall see below, this characteristic derives from the introduction of higher level constructs (which may be used to derive lower order ones). A third major distinguishing feature is to be found in the way the cognitive skills are represented. In essentially all contemporary cognitive formulations cognitive constructs take the form of propositional structures and/or procedural processes. Structural analysis presumes a particular cognitive construct, "the rule", which incorporates both structures and procedures. In addition to combining the advantages of structural and procedural representations, which rules share with "productions" (Newell & Simon, 1972), the rule construct has the important added advantage of having been shown to be especially well suited for representing learning processes and individual differences, and generally for instructional and diagnostic (testing) purposes (e.g., Scandura, 1978, 1980).

To place structural analysis in proper perspective, let me briefly review the general theoretical context of which structural analysis is a part. As emphasized by Scandura (1980), the Structural Learning Theory is not a theory per se. Rather, it is a class of domain (content and subject population) specific theories, which share certain characteristics and common properties, together with the method of structural analysis itself. The latter is an essential prerequisite to any
specific structural learning theory. Individual structural learning theories are characterized by: a) an analyzed domain (i.e., analyzed via structural analysis), b) a general purpose performance test theory, which provides a means for determining what individual learners in the target subject population do and do not know about the domain, and c) certain universal characteristics which affect the way all learners use their available knowledge.

Specific structural learning theories are not only parsimonious, cohesive, precise, and operational, but, given an adequately analyzed domain, numerous tests of such theories have demonstrated their empirical validity. Specifically, under idealized laboratory conditions it has been possible to predict the behavior of individuals in specific situations. For a good historical and philosophical overview of such theories, see Scandura (1980). More details are given in Scandura (1971, 1973, 1977, 1978).

To date, the weakest link in the whole enterprise has been structural analysis. In spite of continuing efforts to make structural analysis more reliable and easier to use, it is nonetheless still true today that its most important single disadvantage, as with all other forms of task analysis, resides in its ambiguity. Different analysts may start with the same task domain, may utilize the same method of analysis, and yet end up with different results. While the degree and kinds of variations that arise may depend to a great extent on the method of analysis that is used, and the relative skills of the analysts, it is fair to say that no method of analysis, including structural analysis, has been entirely systematic or objective.

In the remainder of this article (Part I), I shall review the essentials of structural analysis as it has evolved over the past decade, in the process summarizing some of the results that have been obtained using this method of analysis. In Part II, which will be published in the next issue of THE JOURNAL, I will describe recent advances in structural analysis which move in the direction of increasing systematization and objectification of the process. As this article goes to press, Parts III (empirical test of the method) and IV (empirical test of the resulting analyses) are being planned.

A. THE BASIC METHOD

Much of my empirical research and theory development has been based on prior (sometimes informal mini-) analyses (e.g., Scandura, 1964, 1969) and comprehensive meta-analyses (e.g., Scandura, 1973, Chapters 4–6) designed to expose the structure underlying subject matter content. The name “structural analysis” was a natural outgrowth of these concerns.

Nonetheless, although structural analysis had been used informally in a wide variety of earlier studies (e.g., Scandura, 1964, 1967, 1969, 1971, 1973), the first explicit journal descriptions of the method itself, as opposed to results (structures/processes) obtained by using the method, were published in Ehrenpries
and Scandura (1974) and Scandura, Durnin, and Wulfeck (1974). (The technical reports on which these articles are based were published in February and December of 1972, respectively.)

According to Scandura et al. (1974), the method of structural analysis involves identifying a broad sample of tasks, being "sure that the domains and ranges of each task are fairly explicit. Then . . . explicit procedures (rules) for solving each type of task (are identified). Care (is) taken to insure that these procedures accurately reflect (one's) intuitions as to how intelligent (prototypic) high school students might go about solving the problems."

According to Scandura et al. (1974), "the most crucial step is to identify general parallels among the procedures developed for the sampled problems, . . . and even more important, to devise higher-order rules that realize these parallels as relatively formal but still general procedures." Finally, as noted by Ehrenpries and Scandura (1974) "those rules that are derivable by application of the higher-order rules to other rules in the characterizing set may be eliminated (as redundant)."

Application of this general method resulted in several fairly comprehensive and detailed structural analyses. Our first attempt in this direction was a very practical endeavor. I had just completed a book entitled Mathematics: Concrete Behavioral Foundations (1971b) and the publisher wanted a workbook to parallel the text. Rather than use traditional "seat of the pants" methods, my students and I (Scandura, Durnin & Ehrenpreis, 1971) decided to attack the problem systematically, in the process incorporating some of my ideas concerning higher-order rules. The book itself provided the basis for analysis. First, we went through the text, page by page, identifying the classes of tasks (behavioral objectives) that seemed to be inherent in the material. Next, for each behavioral objective we constructed a solution rule that paralleled the way in which the book would have the students solve them. Third, we looked for parallels among the solution rules. These parallels were used as a basis for identifying what turned out to be a small but potentially powerful set of higher-order rules. These higher-order rules made it possible to eliminate about half of the lower-order solution rules as redundant. That is, using one of the higher-order rules it was possible to derive each of the eliminated solution rules by applying the higher-order rule to some other solution rule.

As it turned out, not only was it possible to identify the basic solution rules and higher-order rules underlying the text but an empirical investigation provided strong support for the analysis (Ehrenpreis & Scandura, 1974). Two groups of elementary school teachers were trained as part of a regularly scheduled summer school course. One group (D) 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 of various types: rules for composing available lower-order rules, rules for generalizing and for restricting lower-order rules.
and rules for forming analogous 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, "The higher-order rules students were taught less but learned more."

As its central importance became increasingly apparent, attempts were made in subsequent theoretical work to formalize the method (e.g., Scandura, Purnin & Wulfeck, 1974; Scandura, 1977). In its essentials, structural analysis begins with a given domain of problems and involves: (1) constructing a sample of problems which are representative of the given domain, (2) constructing a solution rule for solving each of the representative problems (the solution rules being designed to reflect the way in which prototypic subjects in the target population might solve the sample problems), (3) identifying higher-order rules which reflect parallels among the initial solution rules and which operate on lower-order rules, (4) eliminating lower-order rules made unnecessary by the higher-order rules, and (5) testing and refining the resulting rule set on new problems from the problem domain.

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

Sample Problem One

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

[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 Two

Given a line 1, a point A not one the line and a distance d, construct a circle with the radius d which goes through point A and is tangent to line 1.

![Diagram](image)

Fig. 2

Solution Rule Two

[Construct a circle with center at A and radius d]; [construct a locus of points at distance d from line 1 (i.e., a parallel line at distance d from line 1)]; [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 for 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. In the present illustration, for example, both solutions 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 school learners. For this purpose, "locus condition" might 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.)

![Diagram](image)

**Figure 3. High Level Description of Higher-Order Two-Loci Rule.**
Figure 4. Partial Specification of First Decision of Higher-Order Two-Loci Rule.

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 step (5) of structural analysis would require more space than is available, but the general intent is clear. For details of the actual analysis, see Scandura, Durnin and Wulfeck (1974).

Among other things, this intensive analysis of geometry (straight-edge and compass) construction problems demonstrated that the heuristics identified by Polya (1962) can be formulated precisely in the form of higher-order rules. Moreover, it was shown that these higher-order rules, together with a relatively small set of equally explicit lower-order rules, provide a sufficient basis for solving a wide variety of geometry construction problems.

A subsequent empirical analysis (Scandura, Wulfeck, Durnin, & Ehreplies, 1977) further 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 even 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 as is normally the case.

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 types of higher-order rules were considered by Polya (1962). (c) No distinctions were made between deriving solution rules and breaking problems into subproblems. The analysis did not, for example, distinguish between deriving complex solution procedures by chaining component procedures and the widely used technique of breaking problems into hierarchies of subproblems and attacking the subproblems in turn.

B. TYPES OF HIGHER-ORDER RULES

Notice that each of the above solution rules is composed of three corresponding component rules: two locus rules and a goal generating rule. The corresponding higher-rule in this case is a modified higher-order composition rule, which operates on sets of component rules and generates solution rules. As first observed in Scandura (1973, pp. 102–105), this type of parallel is only one of several basic kinds that may be shared by different pairs of rules. Thus, for example, just as higher-order rules may serve to compose component rules, others may serve to extract components from given rules (e.g., Scandura, 1973, p. 103). Higher-order rules of this type would be useful, for example, where a person has learned a rule for solving a relatively complex task as a whole and is faced for the first time with one of the constituent subtasks.

Other types of higher-order rules identified in Scandura (1973, pp. 103–105) include the following:

1. Generalization rules either combine the domains of two or more rules or otherwise extend the domain of a given lower-order rule (by replacing a variable of lesser scope with one of greater scope). This sort of thing happens, for example, where the young child forms the plural of "foot" by adding "s" by overgeneralizing an add "s" rule.

2. Conjunction rules combine into single rules the effects of two or more rules with the same domains. The difference between high-order conjunction and composition rules is that conjunction rules generate lower-order rules in which the component rules are performed simultaneously whereas in the case of composition rules, the component rules are performed sequentially.

3. Elimination rules serve to make lower-order rules more efficient by eliminating redundant subrules. In this regard, subsequent theoretical research (Scandura & Scandura, 1980; Scandura, 1981) shows that the higher-order processes (rules) that are collectively termed "automatization" serve to replace component subrules with more efficient subrules consisting of simpler procedures, but more highly structured domains.

4. Restriction rules do the opposite of generalization rules. They restrict rule domains by replacing variables with constants (or variables of lesser scope).
The procedural portions of such rules then can often be made more efficient via higher-order elimination rules. In current terminology, higher-order restriction and elimination rules correspond to automatization processes — processes by which known rules become automatized (e.g., see Scandura & Scandura, 1980, pp. 29–64).

(5) Selection rules are higher-order rules which select from two or more distinct rules one which the knower deems preferable in the given problem situation.

In listing these types of higher-order rules, I make no claim as to either their exclusiveness or their exhaustiveness. There may be other basic types of higher-order rules that cannot be derived from those above, and certain of the above may be derivable from the others. Moreover, in general, any particular higher-order rule is apt to involve any number of the “purer” types above.

A study by Scandura and Durnin (published in Scandura, 1977) dealt specifically with a variety of powerful higher-order rules. In particular, a total of twenty-four 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 (Brumfiel, Eicholiz, & 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 by 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.

Scandura and Scandura (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. Structural analysis was used first to derive a rule-based characterization of the prototypic concrete operational child. Successive reapplication of the method (see Section C) resulted in the identification of increasingly more primitive sets of lower-and higher-order rules — leading ultimately to a rule-based characterization of the preoperational child. The identification of preautomatized versions of the rules associated with prototypic conservers, and associated automatization higher-order rules, played a key role in the analysis.

In effect, the structural analysis not only provided a (partial but) veridical characterization of competence at two different stages of cognitive development, but also of the transition between them. Given the availability of conservation-type rules associated with preoperational behavior, the analysis provided an explicit basis for training preoperational children to conserve in a manner that was difficult to distinguish from that of natural conservers. Perhaps even 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.²

C. REAPPLICATION OF STRUCTURAL ANALYSIS

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. (See the end of Section A.) At first we were puzzled as to why this had not been a problem in the Ehrenpreis and Scandura (1974) and Scandura (1977) analyses. It later developed that there was a very good reason. Unlike the earlier analysis of my mathematics text, and the subsequent analysis of the Brumfiel et al. Algebra text, the geometry problems were randomly selected from Chapter 1 of Polya's (1962) book on mathematical discovery. The problems, in effect, were not sequenced to facilitate learning but rather to make the points Polya felt essential to his discussion of heuristics.

This recognition opened up a whole new area of concern, fortunately one that could be dealt with in a surprisingly simple way. As noted above in describing the Scandura and Scandura (1980) study, 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 representative of the domain), there is nothing to prevent one from repeating the process. 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 effect, 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 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; 1977).

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. That is, by allowing higher-order rules to operate on lower-order ones
in all possible ways, it was possible to generate a wider variety of new rules and, hence, to solve a wider variety of problems.

Moreover, introducing limitations on processing capacity, or the number of rules that might be active at any given point in time (e.g., see Scandura, 1971, 1973, 1977, 1978), made it possible to generate optimal learning sequences (i.e., to sequence any given set of problems in an optimally learnable order). Comparison of these theoretically derived sequences with both learner controlled and random sequences indicated an approximately two-to-one advantage in favor of the former. This difference was obtained 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. The reason that controls performed less well even under these helping conditions resides solely in the higher-order rules. Success on problems that came later in the instructional sequence required new and more complex higher-order rules as well as the new solution rules themselves. According to the theory, learners who received problems in the prescribed (learnable) order gradually acquired the needed higher-order (as well as lower-order) rules as learning progressed. The less successful control subjects did not.

Footnotes

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1. The materials on which these materials were based were extended and first published as a series of Critical Reading Workbooks by Ann Arbor Press (Scandura, Lowerre & Scandura, 1964). Recently, the workbook materials were further refined and extended, and incorporated into a microcomputer-based individualized learning system. This system was developed under my direction by Instructional Micro Systems, Inc. with the system itself being marketed by Borg-Warner under the trademark “MicroSystem80”.

2. Feibel (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 whereas incongruity training, with its indirect attention to higher-order competence, resulted in learning that more nearly approximated Genevan criteria. The fact that the results of the study referred to groups rather than to individuals, as in the Scandura and Scandura (1980) study, further suggests the need for more detailed and operational analysis of formal operations along the lines indicated above.

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