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Measures of cognitive structure : do they really assess learning at the level of comprehension?

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MEASURES OF COGNITIVE STRUCTURE: DO THEY REALLY ASSESS LEARNING AT THE LEVEL OF COMPREHENSION

A Dissertation Presented

By

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ABSTRACT

Measures of Cognitive Structure: Do They Really Assess Learning at the Level of Comprehension?

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Recently, a group of researchers has begun applying psychometric models and methods to the problem of conceptualizing and measuring subject matter structure, students' cognitive structure, and their correspondence. Word association, graph construction, and/or card sorting tasks, for example, have been used to obtain similarity judgements of key instructional concepts. The analyses of these judgements, which can result in graphic or otherwise pictorial representations, are then taken to reflect students' internal organizations--cognitve structure-- of those key concepts. Studies to date have shown that this cognitive structure changes as a function of instruction, that it is related to field independence, that it changes as a function of organization of the instruction, and that the methods used thus far to measure it produce similar results. What has <u>not</u> been indisputably demonstrated, however, is whether these measures in fact tap aspects of structure related to comprehension and subsequent learning on the level we, as educators, generally want to measure.

It could be the case, for instance, that the level of structure tapped is learned by rote with no real comprehension of the material required. If that were true, cognitive structure might appear to approximate content structure but recall would be low. If, on the other hand, these measures do tap appropriate structure, then they should be able to discriminate among students in different states of learning after equivalent instruction. The first purpose of this study, therefore, was to determine whether the cognitive structure that is revealed through the application of this methodology is indicative of student comprehension and learning, or whether it can be trained without the student's full understanding, and subsequent learning, of the relevant material.

The second purpose of the study was to apply this psychometric methodology to a learning situation that has produced a nonspecific facilitative transfer effect. While the effect has been discussed in terms of initially presented information serving as a knowledge "bridge" between what students already know and the difficult material they are asked to learn from a second passage, what actually transfers from the first to the second passage is not clear. Measuring the cognitive structure created by the learning of these passages in both facilitative and nonfacilitative conditions, then, should bring some insight to the question of what nonspecific transfer really is.

Five groups of 20 students each read two prose passages, completed a word-association and a graph construction test on each passage, and took a recall test on the second passage. All students read the same, difficult-to-comprehend second passage, but the first passage varied over groups. Students initially read either a concrete or abstract passage, crossed with instructions to underline key concepts or not, or they read a structure-training passage, designed to train cognitive structure without requiring comprehension of the material.

Results of the recall and proximity tests indicated that the sort of cognitive structure assessed by proximity measures _can_ be trained to correspond to content structure, but that subsequent recall remains low. The nonspecific facilitative transfer effect was replicated, but an additional interaction with the underlining variable also appeared. Those who underlined in an already facilitative condition, in other words, learned even more while underliners in the nonfacilitative condition learned even less than non-underliners. While caution is advised in using this methodology to assess school-type learning for instructional decision-making, since comprehension is not always implicated in their results, other potential applications of these measurement techniques are discussed, along with some of the problems of interpretation they raise. The relationship between cognitive structure as defined here and learning of various sorts still has potential in educational assessment and therefore warrants further investigation.

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CHAPTER I

INTRODUCTION

"In the course of the development of curriculum in education, the concept of knowledge structure has been at the forefront of a great deal of thinking. It is an expression that has been variously interpreted" (Smith, 1964, p. 2). Curriculum developers generally agree, however, that learning the "structure" of a discipline, as opposed to rote facts, requires full understanding of a subject matter and hence leads to better retention, facilitates problem solving, and results in better transfer of skills to new situations. But in order to teach subject matter structure so that retention, problem-solving, and skill transfer may be facilitated, we need to know a little more about what we might mean by structure--both of the content discipline and its representation in memory--and how to measure it. How researchers have approached the conceptualization of knowledge structure has, in part, depended upon the research tradition within which they are working (Perkins, Note 1). Cognitive researchers, for example, are generally concerned with building theories of semantic memory and have therefore viewed knowledge structure and representation within that context. Their emphasis has been on determining, often in the minutest detail, the form information takes as it enters the head and the cognitive operations that act upon it. Educational researchers, on the

other hand, are more interested in the facilitation of learning, the effect particular manipulations of instructional materials will have on some performance measure of learning. Structuring the conditions under which learning will be made more effective has been the focal point of their endeavors, while they have paid scant attention to what may actually be happening in the student's head as learning takes place. (See Perkins, Note 1, for a complete review of the literature defining, using, or implicating "knowledge structure.")

Recently, however, an approach has arisen whose end is to arrive at a conceptualization of structure that will permit valid measurement of the structure in the content material, the representation of that structure in the student's head following learning, and the degree of correspondence between the two. It is an approach originating within psychometric theory. Rather than formulate a theory of semantic memory or specify the situational conditions under which learning is improved, a group of investigators coming from a psychometric perspective are viewing questions involving knowledge structure as fundamentally problems of measurement. Methods should be developed, they argue, that will measure both the structure inherent in instructional material and the structure resultant in the learner's head following the learning of the material in such a way as to render them comparable. With the ability to judge the correspondence, or lack thereof, between content and cognitive structure, the potential

for the evaluation of learning outcomes and subsequent educational decision-making is great. The structure of students falling into different groups, however defined, can be compared; structures of students can be compared to structures of teachers; and structures of students can be compared to subject matter structure. And with the results of these comparisons, we might begin to reliably determine where learning has failed or misunderstandings exist or how other student variables may interact with the structuring of information in memory.

The two crucial questions raised by this approach are, of course: 1) what methods are available and appropriate for measuring content structure, and 2) what methods are available and appropriate for measuring cognitive structure. And the corollary question to both of these is, what are we going to accept as a definition of knowledge structure? To answer the last question first, forerunners in the application of psychometric models and methods to issues in cognition have almost exclusively accepted the thesis that meaning is relational in structure. Garner (1962) states that words or events become meaningful only as they acquire relational structure, and that structure is <u>not</u> just the sum of the significations of individual words. Deese (1965) asserts that meaning consists of relations between linguistic events and that we "must find ways of reducing the organization inherent within collections of words to underlying patterns" (p. 65).

And Fillenbaum and Rapoport (1971) speak of language as a system of relations in that the meaning of an item is a function of the set of meaning relations which hold between that item and other items in the same semantic domain. Because of the interest in and importance placed on how large chunks of information are processed, how learning relates to a broad context, psychometricians interested in cognitive structure have chosen to study unit-sized bits of instruction--rather than words, sentences, or paragraphs--and have therefore accepted the relational structure existent among major concepts in the instructional material as being "knowledge structure."

Determining precisely what methods are available and appropriate for the measurement of content and cognitive structure is essentially the raison d'etre of the studies in this area. The early studies on the measurement of concept association and relatedness (P. E. Johnson, 1964ff) were aimed at establishing word association measures as useful indicators and predictors of student understanding of relatedness among instructional concepts. The later research (represented by Shavelson, Preece, Rudnitsky) built upon the results of earlier work and set about applying more sophisticated measurement techniques and analyses to the structure measurement problem. Just what methods have been applied, and how they have been used, in specific situations, then, is the question that warrants review. Further, the entire

issue of the efficacy of applying psychometric models and methods to problems in cognition demands some additional consideration.

Studies of Associative Meaning

Johnson (1964) was one of the earliest to accept and promote a relational structure of meaning within a subject discipline and, as such, was one of the first to use a word-association measure as a way to tap student understanding of that structure. He operated from the thesis that conceptual relationships among words in a subject matter like physics would provide a powerful constraint on how words defining the physics concepts are used. Accordingly, the degree to which students understand these conceptual relationships should be reflected in the extent to which they interrelate concepts consistent with the system. Correlating the number of interrelated associations given by students on a word association (WA) test with the students' degree of involvement in physics, then, Johnson (1964) showed that those students who were currently taking physics produced more interrelated associations than students who had already taken the course; those students, however, produced more interrelated associations than students only planning to take physics, who in turn generated more than students who had neither taken physics nor were planning to.

Johnson (1965) investigated the usefulness of the WA

test as an index of school learning by examining the extent to which problem solving in physics was related to specific patterns of concept associations produced by students. While a relationship was found, it was not a uniform one. Good problem-solvers generally produced more interrelated associations than poorer problem-solvers except when the problem solving test was administered before the WA test; in this condition, some concepts elicited more responses from the poorer problem solvers, bringing their WA performance closer to that of the good solver. Johnson concluded that some concepts are more dependent on general language habits than others and whether this dependency was interfering or facilitative remained to be seen.

It was in his 1967 study that Johnson really began to address himself to theproblem of measuring the overall conceptual structure that students might have in memory as a result of having learned relationships among subject matter concepts. Concepts, says Johnson, are defined through their relations with other concepts, and the logical structure of any given set of materials is determined by the interrelations among concepts as formally specified by the constraints within the materials. The types of constraints that Johnson keeps referring to are things like the formulas that appear in physics instruction, dictating exactly how certain concepts are to be related. Learning, then, consists of internalizing these interrelations, so that individuals at different levels

of achievement should exhibit differences on measures of concept interrelatedness. Furthermore, since the theoretical structure of a discipline serves as a framework for relating concepts to experience, these differences should correlate with empirical characteristics of the content material; high achievers, in other words, should be more likely to exhibit concept associations similar to those occurring in the instructional material than low achievers. And results in Johnson (1967) and Johnson (1969) were consistent with these hypotheses.

Before proceeding with Johnson's last study, it seems appropriate to include a few remarks about the measure of concept interrelatedness that Johnson used and which will appear in a good many later studies. A WA test is typically one which consists of a number of stimulus words, to each of which students are instructed to respond with as many related words or concepts as they can. Results of the test, then, are in the form of lists of response words corresponding to each stimulus word. And measuring the degree of relatedness among stimulus words is done through the use of a relatedness coefficient (RC) developed by Garskoff and Houston (1963). The RC is "designed to capture the general level of verbal relatedness regardless of the specific kinds of relationships which may exist between the words under consideration" (p. 279) and is a function of both the responses two stimulus words have in common and their relative position

within the respective response hierarchies. Two stimulus words to which a student has responded with many of the same concepts, in other words, would have a higher RC and would be considered to be more highly associated or more similar than two stimulus words with little or no overlap in their response distributions.

Johnson, Curran, and Cox (1971), the final study in this series, present a specific model for how a set of concepts are interrelated in Newtonian mechanics. Their model is based mostly on the formula constraints within the instructional material and simply shows which concepts are associated with which other ones and how closely. Johnson et al. then proceed to demonstrate that their model will account for word association and concept similarity judgments given by students of Newtonian mechanics.

A general conclusion that can be drawn from Johnson's studies seems to be that defining subject matter structure as a relational one involving the major concepts in the discipline and using word association measures to assess the learning of that structure constitute a viable approach to evaluating high-order school learning. Certainly any subject matter has a set of fundamental concepts related to one another in such a way as to comprise an overall structure of the subject, and if association measures can begin to assess learning of that structure, more sophisticated and accurate measures with significant educational implications might well

be in the offing.

Measurement of Content and Cognitive Structure

Shavelson. According to Shavelson (1972), "a critical problem in the development of curriculum and in the formulation of instruction is that of how to structure a body of knowledge so that communication of this knowledge to the learner can be effective, and his learning correspondingly efficient" (p. 225). The approach to this problem, he goes on to say, has typically been to study the structure of memory and the processes of learning and then make recommendations regarding the use of this postulated structure and these hypothesized processes in instruction. While there is nothing inherently wrong with this approach, the critical question it raises--i.e., what is, in fact, the correspondence between content structure and structure in memory--has not been studied directly, and it is this question that concerns Shavelson. His assumption is that if learning is efficient, then the content structure of the material and the conceptual structure in the student's head should match. Following Johnson's lead, he very specifically defines content structure as "the web of concepts (words, symbols) and their interrelations in a body of instructional material" (Shavelson, 1974a, p. 111) and cognitive structure as "a hypothetical construct referring to the organization (relationships) of concepts in memory" (Shavelson, 1974a, p. 116). Of

concern at this point is searching for a set of techniques which will 1) represent content structure as interrelations among concepts, ideas, or propositions, since "any notion of structure rests at least as much on these interrelations as on the words themselves" (Shavelson, 1974a, p. 112); 2) produce data consistent with the definition of cognitive structure; and 3) yield content and cognitive structure data in forms comparable to one another. And most of Shavelson's studies, to which we now turn, have been directed toward finding such a set of techniques, along with demonstrating their use.

Shavelson's initial two papers (1972, 1973) present the same study from two different slants. The 1972 paper gives the purpose of the study as being to examine the correspondence between analyses of content and cognitive structure, while the 1973 paper cites the purpose as being to extend Johnson's results by collecting WA data over an extended period of learning and by collecting aptitude data, both to provide information about student learning from text. Basically, the study consisted of a six-day period of instruction and testing. On the first day, all the students were given a series of four aptitude tests, one or another version of a 30-item physics achievement test, and a word-association (WA) test containing 14 key physics concepts. Over the next five days, the students in the instruction group read five consecutive instructional packages taken from a standard physics

textbook, and at the conclusion of each day, they received a WA test; at the end of the sixth day, they also took the other form of the achievement test. Control subjects received the same tests as the instruction group but in a period of three days total, instead of five. Twenty-eight students were assigned to the instruction group and twelve to the control group.

The achievement test data collected in the study and its analysis were reported in both the 1972 and 1973 papers. Results were that no performance differences existed between instruction and control groups at pretest and none were evident between pretest and posttest for the control group; the students in the instruction group, however, did improve their scores significantly from pretest to posttest. From here, treatment of the data diverges between Shavelson's two papers. In order to examine a correspondence between content and cognitive structure, Shavelson (1972), via digraph analysis[1], constructs first an adjacency and then a distance matrix of the 14 major concepts in order to represent information about the content structure. Cognitive structure is represented through an analysis of WA test data; Shavelson calculates relatedness coefficients (Garskoff and Houston, 1963) for pairs of stimulus words, providing the degree of

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[1]Digraph analysis is explained in greater depth in one of Shavelson's later studies. It seems more appropriate to discuss it in relation to that study rather than treat it in any great detail now.

response overlap among concepts for each subject, and then constructs a median RC matrix for each day of the instruction and control groups. Shavelson predicts that word interrelatedness should increase across the board for instruction subjects as days progress, and judging from a median RC per day, that indeed happens for the instruction group but not for the control group, whose median RCs do not change over days. Shavelson also compares entire matrices through calculations of Euclidean distances between them. Results of these comparisons indicate that control group matrices change little over days whereas those of the instruction group shift considerably, becoming closer in structure to the distance matrix of the content structure over days. Shavelson concludes that the content structure does indeed influence the organization of concepts in memory, given that the cognitive structure of students changed over the course of instruction and moved in the direction of the content structure. One cautionary note buried in his discussion which will bear weight later on, perhaps, is that "the evidence does not suggest a near perfect correspondence between content structure and cognitive structure" (Shavelson, 1972, p. 233).

After reporting the achievement test data, Shavelson (1973) does a number of seemingly peculiar analyses on the WA test data. Prior to any formal analyses, Shavelson divides the 14 key concepts into two groups on the basis of how frequently they appeared in the instructional material.

Then, in reducing subject response data, he averages the number of responses given to low frequency concepts, both for each day of instruction. After plotting the mean frequency of response as a function of days and frequency of concept occurrence (high or low) for the instruction and control groups, Shavelson then computes a 28 x 6 x 2 (instruction subjects x days x frequency of occurrence) analysis of variance, with days and frequency of occurrence as within subjects variables. The graph shows an increase in mean response frequency for instruction subjects over days but not for control subjects, and results of the analysis are a significant main effect for days, a frequency of occurrence effect (although the .08 difference between the means is hardly of practical significance), and a frequency x day interactions. Following this analysis, the WA data are rescored in terms of constrained and unconstrained responses; a constrained response was one in which the term was an element of a defining equation for one of the stimulus words. What was scored, then, was the frequency of constrained and unconstrained responses in the upper and lower halves of student response distributions (i.e., first versus last responses), with the assumption that responses in the lower half are harder to retrieve than those in the upper half. Shavelson again plots mean frequency of response in upper and lower halves of the response distribution across days for the instruction and control group subjects. And

he repeats the 28 x 6 x 2 ANOVA, with response distribution position taking the place of the frequency of occurrence variable. Again, both the plot and the analysis show a day main effect, and the analysis also shows a distribution position main effect, with more constrained responses appearing from the upper position than from the lower. Shavelson is never quite clear as to exactly why these last two analyses were done, and they do not seem completely justified.[2] That there is an effect of instruction across days in the number of responses given would appear reasonably evident and is already supported in the achievement test data: instruction students did learn physics concepts; control subjects did not. It would also seem obvious that the number of responses given to words that appeared frequently in the text would be higher than the number given to words appearing infrequently; similarly, if responses in the lower position of the distribution are assumed to be more difficult to retrieve, then finding that constrained responses occur more frequently in the upper portion than in the lower should come as no surprise. It simply is not clear just what these analyses offer towards improving our understanding of how concepts are interrelated and structured in memory.

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[2]Shavelson also errs in presenting the tabled results. The frequency of occurrence and response distribution variables are listed as between subjects variables, when, in fact, they are within subjects variables.

Before moving on from this study (Shavelson, 1973), the additional analyses performed by Shavelson need to be discussed briefly. Shavelson correlates students' scores on the WA tests, specifically frequency of occurrence and constrained response position, with their posttest achievement scores, and finds that constrained responses in the upper position correlate most highly with achievement (.35). Since the response trend shows students with higher achievement scores giving more upper distribution constrained responses early in instruction, Shavelson suggests that the WA test could reflect learning of concept meaning and finding efficient means of storing those meanings. If constrained responses are taken as an indication of storage efficiency (i.e., storing concepts by equation), then one would expect students with low achievement scores to give fewer upper distribution constrained responses, as did happen here. Finally, relating aptitude to achievement and WA data of instruction students, Shavelson found that 1) there were few correlations between aptitude and WA test data: abstract reasoning through the hidden figures test proved to be the most highly related to WA; 2) verbal ability was the best prediction of pre- and posttest achievement; and 3) abstract reasoning was related to post- but not pretest achievement. What all these results suggest to Shavelson is that for students who performed well on the achievement test, physics concepts became more meaningful early in instruction.

The next four studies by Shavelson (Shavelson, 1974a, b; Shavelson & Geeslin, 1975; Shavelson & Stanton, 1975) speak mainly to the issues of what techniques are best for measuring content and cognitive structure and, then, how to validate them. Shavelson (1974a) and Shavelson & Geeslin (1975) both review a number of ways of representing content--hierarchically, categorically, and graphically via tree diagrams, to name a few--and then settle upon the use of directed graph theory (Harary, Norman and Cartwright, 1965) to best depict interrelations among concepts in a subject matter. Justification for using digraph theory in this situation may come for Harary _et al_. (1965) themselves, as they state that digraphs serve as mathematical models of structural properties of any empirical system consisting of relationships among pairs of elements. Furthermore, they believe that "despite the widespread use of structural concepts in the social sciences, it is fair to say that the formal analysis of structure has been relatively underdeveloped in these fields. The technical terminology employed in describing structures is meager; few concepts are defined rigorously. As a consequence, the social scientific description of structural properties tends to be couched in ambiguous terminology, and detailed studies of structure, as such, are rather rare" (Harary _et al_., 1965, p. 1). Digraph theory, therefore, may provide a means of depicting physics content structure not only for the purpose of assessing learning of that structure

but also for studying structure itself in this discipline.

Shavelson (1974a) and Shavelson & Geeslin (1975) work through the process of digraph analysis using examples of content from their overall program of research to show how content structure was arrived at, and a summary of that process bears repeating here. The basic steps in the analysis are to 1) identify the key concepts in the subject matter (this is usually a matter of judgment on the part of a content expert), 2) identify every sentence in the instructional material containing two or more of the key concepts, 3) diagram each sentence using a standard grammar (e.g., Warriner & Griffith, 1957), 4) convert each sentence into a digraph by using the set of rules that Shavelson and Geeslin (1975) append to their paper, 5) from the digraphs, determine the shortest distance between each pair of concepts and enter this into a distance matrix, and 6) convert the distance matrix to a similarity matrix via a simple transformation. Constructing the matrices from the digraphs is also explained fairly thoroughly in Harary et al. (1965). The resulting similarity matrix, like the matrices produced from WA data, can then form the basis of any number of analyses, including multidimensional scaling, hierarchical clustering, and graphic representation. These will be considered in greater detail somewhat later in the paper.

Shavelson (1974a) demonstrates the use of digraph analysis on operational systems content, and Shavelson and

Geeslin (1975) extend it to include content in physics and probability theory. Both papers then present preliminary validation data which indicate that several different means of tapping cognitive structure--namely word association, graph construction, and card sorting (card sorting is eventually thrown out since, in these studies, it tended not to produce discriminative data)--yield similar structures to one another and to the content structure when administered to the two curriculum experts who developed the instruction.

The two specific methods of measuring cognitive structure are presented and discussed in Shavelson (1974b) and Shavelson & Stanton (1975), the purpose of the latter also being to provide systematic evidence for the validity of the techniques. Shavelson (1974b) describes in detail the word association and graph construction tests and the sort of data they will produce. The WA test has been described in connection with Johnson's use of it, but Shavelson presents additional ways of scoring subject protocols, i.e., scoring for the total number of responses per stimulus word, the average number per stimulus word and the number of responses of a particular type per stimulus word, as well as the overlap of response lists for pairs of stimulus words (the relatedness coefficient of Garskoff and Houston, 1963). The graph construction test (GC) also consists of responding to a series of key stimulus words, but the response here

involves manipulating the concepts to produce a graphic structure with (labelled) lines interconnecting similar concepts. Fillenbaum and Rapoport (1971) present, in greater detail, the statistical properties of the sorts of graphs resulting from this task, but, basically, both the WA and GC tests produce similarity or proximity data that can be subjected to the same kinds of analyses as used on the content structure data. The card sorting task first mentioned by Shavelson (1974a) and appearing again in Shavelson & Stanton (1975) is one in which subjects are handed a set of cards printed with the key concepts encountered in the instructional material. They may then be told either to sort the cards into a defined number of piles or into any number of piles that they think are necessary. Clustering analyses and latent partition analysis then produce data bearing on the perceived similarity among concepts. Unfortunately, the small number of cards used in the Shavelson studies and the fact that they were sorted into only two piles limited the usefulness of this technique for measuring cognitive structure.

Regarding the validation of the above techniques as measures of cognitive structure, Shavelson (1974b) again presents the same preliminary results that he presented in the last two studies. A more complete description of results, however, is given by Shavelson and Stanton (1975). After obtaining an analysis of the content structure on

operational systems, they administered the WA, graph construction (GC) and card sorting tasks comprised of operational systems concepts to the two curriculum experts mentioned previously. Up to and including this paper, Shavelson has preferred to use a hierarchical clustering solution for the distance or similarity data, and he presents the tree structure representations for both the content and cognitive structures. Hierarchical clustering (S. Johnson, 1967) is a procedure for grouping concepts into clusters on the basis of similarity coefficients. On the basis of a series of coefficient cutoffs and a recalculation of coefficients at each level of the hierarchy, clusters are merged at successively higher levels so that one cluster eventually incorporates all of the smaller ones. Prior to presenting any data, though, Shavelson and Stanton (1975) briefly review construct validation methodlogy and rightly assert that "the construct definition sets the boundaries for potential measurement techniques and data interpretations" (p. 67). Furthermore, one method, among several, of investigating rival construct interpretations is to correlate scores on different measures of the same construct; presumably, if the techniques are all measuring basically the same construct, then the correlations among the scores should be reasonably high (convergent validity criterion). This is the approach that Shavelson and Stanton take, and they expect to show that the WA graph-construction, and card sort tasks all yield

similar structures of the same concepts, thereby giving evidence of construct validity. "Convergence of representations was determined by a qualitative or nominal comparison between graphs" (Shavelson & Stanton, 1975, p. 76). Without actually calculating any formal correlational analysis, they conclude that there is a "close correspondence" between the content structure representation and the WA and GC cognitive representations, as well as between the GC and WA representations themselves (because of the failure of the card-sort task to produce data that could be analyzable by hierarchical clustering, it will not be discussed further).

Shavelson and Stanton attempted to "replicate" this finding with a different sample of subjects and so administered the same series of tasks to a group of mathematics teacher interns enrolled in a mathematics curriculum course. Although Shavelson and Stanton claim to have provided additional evidence of the convergence of the GC and WA tasks, there are all manner of problems with their "replication" and conclusion. First, they administered an achievement test to the interns and established that the subjects had indeed mastered the content material prior to participating in the study; four paragraphs later, however, they announce that the interns had built graphs before and after studying curriculum on operational systems and that there are differences in their cognitive representations between pre- and posttest. Not only is it unclear where the pretest data is coming from,

it is less clear as to exactly how knowledgeable the interns are in operational systems. If they have indeed mastered the content as is initially suggested, then to exhibit differences in cognitive representation between "pretest" and "posttest" is quite contradictory (there would even be some question as to why a pretest was given). On the other hand, if the interns learned concepts in operational systems between the administrations of a pre- and posttest, then when was the achievement test given and what was its purpose? These questions would appear to be important ones to answer before the data can be of much use. In addition, claiming close correspondence or lack of correspondence between representations simply on the basis of what appears to be eyeballing the data is questionable at best. From the tree-structure diagrams that Shavelson and Stanton (1975) present, it is not easy to see what is being judged as correspondence. The structures that are exhibited as being dissimilar do not seem to be any more different than those that are claimed to be corresponding. That Shavelson and Stanton (1975) have actually demonstrated convergent validity of their measurement techniques, then, is debatable.

The remaining two studies that are further extensions of Shavelson's work are Geeslin and Shavelson (1975) and Stasz, Shavelson, Cox and Moore (1976). The purpose of Geeslin & Shavelson was to extend the use of the techniques for measuring structure to the area of mathematics instruc-

tion, where there is an emphasis on communicating a mathematical structure to students but little empirical examination of that learning. Following the example set by previous studies, Geeslin and Shavelson (1975) use digraph theory to analyze the content structure of the probability theory instruction that was chosen. One difference, however, is that they choose to obtain a multidimensional scaling solution as a representation of the structure, rather than a hierarchical clustering solution, giving as justification only the belief that a multidimensional scaling solution is more consistent with their interpretation of the subject matter. Cognitive structure was represented by multidimensional scaling solutions of relatedness coefficient matrices obtained from word association data. Half of the 87 junior high subjects studied the text on probability over a period of days (the experimental group) while the remaining half studied a programmed text on an unrelated mathematics topic; data on achievement and attitude were also collected. Results of a nonparametric analysis of variance performed on Euclidean[3] distance data at pre- and posttest indicated that the cognitive structure of subjects in the experimental group was more similar to the content structure than was the cognitive structure of control group subjects after instruc-

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[3]Euclidean distances are calculated between entire matrices with smaller distance scores indicating closer relationships between the matrices. In this case, RC matrices (cognitive structure) were compared with digraph similarity matrices (content structure).

tion. Correlations between attitude scores and scores on other variables were generally low, and those between achievement and correspondence variables were low, the latter perhaps indicating that "learning to solve problems [achievement] and learning of mathematical structure [evidence by cognitive and content structure correspondence] represent different aspects of learning" (Geeslin & Shavelson, 1975, p. 37).

Finally, Stasz et al. (1976) "investigated the correspondence between content and psychological structure of individuals who differed with regard to a particular cognitive style--field independence or dependence" (p. 551). The basic assumption here is that students of different cognitive styles may not differ from one another in overall ability but they do differ in the way in which they learn. It might therefore be expected that the achievement scores of these students after learning some content would be similar while their cognitive representations of the material in memory would differ in systematic ways. In addition, the cognitive style of the teachers communicating the content structure might be expected to interact with students' learning of structure. The procedure of this study differed from that in previous studies, in that content structure was represented only by four labelled clusters of important anthropological concepts (the content in this study was a specially prepared social studies minicourse on the Mayan civilization),

and cognitive structure was measured by a similarity judgments task involving pair-wise comparisons of the key concepts on an 11-point rating scale. These ratings were then subjected to a multidimensional scaling routine to yield three-dimensional representations. Achievement tests and measures of cognitive style were also administered. While results of the achievement test showed no differences between field-independent (FI) and field-dependent (FD) groups of students, although a difference between pre- and posttest due to learning is evident for both, the cognitive representations for the two groups were judged to be different. It is again unclear as to what criterion was used to make such judgments, but the cognitive structure of the FI students was judged to be more similar to the content structure than that of the FD students, whose configurations showed more clusters and less differentiation between clusters. It was also the case that the structures of the teachers were more similar to the students than to the content structure, which surprised the authors. Given the fact that the teachers knew no more about the instructional material than the students until they were required to teach it, and therefore cannot truly be called "experts," this result should not be altogether surprising. In conclusion, Stasz et al. suggest that the cognitive style variable and its measurement through these techniques be used in Aptitude x Treatment interaction research, as well as in research on cognition and the acquisition of knowledge. But

since the evidence of the validity of these measurement techniques is still arguable and they have not yet been demonstrated to detect differences in achievement levels, this potential use is still open to question.

Preece. Following in the spirit of Shavelson and his colleagues and their use of hierarchical clustering and multidimensional scaling analyses of concept similarity data, Preece (1976a) adds another type of solution: the application of Waern's (1972) graphic representational analysis to proximity data. Like P. Johnson and Shavelson, Preece accepts the definition of cognitive structure as the pattern of concept interrelatedness in memory and the basic assumption that education involves the building and rebuilding of structures. As a result, he, too, is concerned about the methodological problems in trying to measure the cognitive structure in students' heads following their learning of content. But Preece argues that while a spatial or hierarchical analysis may be appropriate *a priori* to some semantic domains, a graphic representation (*a la* Waern, 1972) is more suitable for domains where a spatial or hierarchical structure is not necessarily suspected *a priori*. In his study, then, Preece adopts the graphic representation solution for use with data collected on free and controlled word association tests and on a tree-construction (like Shavelson's graph construction) test in the domain of mechanics concepts.

In order to compare results of the students' performance on the three types of tests, Preece (1976a) calculated, for each subject, RC proximity matrices (weighted and unweighted[4]) for the WA tests and interconcept separation matrices (direct and square-root) for the tree-construction test. From these, he computed mean concept interconnectedness and mean concept separation indices for each subject. Correlating the individual indices of connectedness and separation, Preece found high correlations between weighted and unweighted indices of the WA tests and between the direct and square-root distance indices of the tree-construction test but rather low correlations across the different types of tests. Using the entire proximity or separation matrices and comparing group averages, on the other hand, Preece found high correlations across test types. His interpretation of these results was that the former was explainable in terms of task constraints placed upon subjects and the latter constituted evidence for the validity of these tests as measures of cognitive structure. Using the cognitive structure data in the graphic representational analysis also produced configurations that Preece claims were "well represented by the proposed digraph model" (1976a, p. 7). One problem with these interpretations, however, is that the three different types of tests were administered at three different times: the

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[4]Weighting simply put more emphasis on the initial responses in subjects' WA lists.

free WA test immediately following course instruction, the controlled WA test three weeks later, and the tree-construction test at least one week following the controlled WA test. Since no previous studies have tackled the problem of structure retention or the possibility that structure might change as links between concepts are forgotten, correlations across test types in this study become hard to interpret. Low correlations might be a function of structure change; high correlations might be evidence for structure retention. This is an issue that Preece fails to consider when discussing his results. It also appears that his comparison of cognitive and content structure configurations was an eyeballing judgment.

In a brief critical essay, Preece (1976b) argues against the use of a Euclidean distance analysis in Shavelson's earlier data comparing content to cognitive structure over days. According to Preece, such an analysis would yield an apparent change in distance between matrices over days even when no learning had occurred over those days. The alternative type of comparison, he asserts, is a direct correlation between the proximity matrices. This is an issue, though, that still appears unresolved; it is simply unclear as to which comparison would be more appropriate.

Rudnitsky. The emphasis on methodological issues in analyzing content structure and assessing cognitive structures continues to be a dominant theme in several studies by

Rudnitsky. Rudnitsky (1976) first used Shavelson's techniques with two instructional presentations in the realm of botany, investigating the power of the techniques to discriminate between two organizations of the material. The digraph analysis of content structure did not discriminate well between the two versions of the botany unit, which was judged to be a function of the fact that the analysis is based on sentences and few actual sentence differences existed between the two versions. But the findings of differences between cognitive structure configurations led to the reanalysis of the data presented by Rudnitsky and Garlock (1977). Here it was suggested--and this suggestion is completely consistent with Shavelson's hypotheses--that "content structure might interact with certain cognitive attributes of learners" (p. 5). The type of content organization might be expected, in other words, to affect some learners to a greater extent than others, depending upon, for instance, the amount of prior knowledge had by the learners. Like Preece, Rudnitsky and Garlock (1977) use Waern's (1972) graphic representation as an approach to visualizing the content and cognitive structures. Interestingly, they mentioned using multidimensional scaling solutions to arrive at a more "inflexible" configural orientation, since Waern's technique leaves orientation to the discretion of the user. Yet, multidimensional scaling routines typically do not determine axis orientation. Rather, distance between points

is scaled in one to n number of dimensions, depending on the routine and specifications of the user, and it is up to the user to decide upon the most meaningful number of dimensions and axes orientation.

Rudnitsky and Garlock's reanalysis, then, consisted of breaking Rudnitsky's (1976) original groups into subgroups on the basis of their recall scores on the achievement test (high vs. low scorers) running matrix correlations between their respective cognitive structures and between their cognitive structures and the two content structure organizations. From the pattern of the results, Rudnitsky and Garlock conclude that different types of content organization not only produce different cognitive organizations but that they have a differential effect on students at different achievement levels. While the former of these two conclusions seems warranted in that a concept-related organization appears to have had a greater effect on cognitive structure than a world-related organization,[5] that high-recall subjects were affected differently from low-recall subjects is a questionable interpretation. The cognitive structures of both high-recall groups do show a greater relationship to the concept-related organization than to the world-related organization, but so do the low-recall groups and the cor-

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[5]See Rudnitsky (1976) or Rudnitsky & Garlock (1977) for a discussion of the difference between these two organizations in their instructional material.

relation differences are nearly the same in both low- and high-recall groups. It is true that correlations involving the high-recall groups and the content structures were across the board higher than those involving the low-recall groups, which Rudnitsky and Garlock do point out. But this would merely suggest that high-recall students are generally better able to assimilate new information to existing structure than low-recall students.

Rudnitsky (1977) attempts to show a little more systematically what Preece (1976a) argues, namely that some representational strategies may be more appropriate than others within particular semantic domains. Hierarchical clustering and multidimensional scaling were the techniques chosen by Shavelson and his associates to represent interconcept relations in mathematics and physics, but the graphic analysis was preferred by Preece (1976a) and Rudnitsky (1976) because it seemed more appropriate to use with instructional material that has less clearly defined concept relationships or a less obvious apparent structure type. Rudnitsky (1977), however, proposes to compare all three representational methods--hierarchical clustering, multidimensional scaling and graphic analysis--within one subject domain: botany. Comparisons across technique can then be made, as well as comparisons between content and cognitive structure within each technique.

Rudnitsky re-presents his (1976) data by each of the

three techniques and follows them with a minimum of verbal description of mostly visual comparisons, since "what matters to the researcher is what the representation looks like" (p. 6). He concludes that hierarchical clustering is a less useful method of representation for botanical concepts than the other two since it emphasizes taxonomic structure, class inclusion, that is not a strong feature of botany. Both graphing and multidimensional scaling, on the other hand, emphasize concept interconnectedness and similarity (respectively); both, then, afford greater insight into the sort of structure Rudnitsky's material has. Because conceptual structure involves relationships (connectedness) and proximity (similarity, clustering), Rudnitsky (1977) tries out a combination of the scaling and graphing approaches in order to capture the overall structure in one picture. "While not geometrically neat," he says, "these representations do combine the strengths of scaling and graphing and result in a 'picture' that is capable of being compared to other 'pictures' in terms of relationships, clusters, proximity, and orientation" (p. 22). The problems with this approach are, again, the same ones that have surfaced in previous discussion with respect to earlier studies. How are we to interpret the resulting structures and on what criteria are we to judge differences and similarities among structures? Multidimensional scaling presumes underlying dimensions which should be identified to maximize structure meaningfulness;

yet, it is not clear _how_ they should be, unless specific _a priori_ dimensions are suspected. Similarly, the linkages between concepts resulting from a graphic analysis do not indicate the type of relationship that exists between the concepts, only that there _is_ one. Finally, in making comparisons of relationships, proximity, clusters, and orientation between types of structures (content vs. cognitive, cognitive of high-recall students vs. cognitive of low-recall students, etc.), how similar is "similar"? How different is "different"? What does one type of difference mean with respect to another type of difference? We simply do not yet have any kind of criteria upon which to base those sorts of judgments.

Other Related Studies

Related to the mainstream of research on measuring content and cognitive structure are several isolated studies having a common theme: how does memory structure change over the course of instruction and the learning of new material? Loftus and Loftus (1972) assume a hierarchical network model of semantic memory, but they diverge from the usual reaction time experiments investigating retrieval differences among well-learned categories of words or concepts. Instead, they ask whether retrieval patterns will differ as a function of how well learned the material actually is; pattern differences would indicate that students change their overall

knowledge structure as they learn new information. In a study using well-known psychologists and their fields of study as the stimulus material and testing graduate students who differ in the number of course credits in psychology they've taken, Loftus and Loftus (1972) showed that the retrieval pattern of advanced students was clearly different from that of beginning students. Advanced students more quickly responded with an appropriate psychologist's name when given the area of study and then the first letter of the name, whereas beginning students favored a letter-first/area-second presentation. And the former pattern resembles more closely the pattern observed for well-learned material, from which Loftus and Loftus infer that "one of the consequences of instruction may be to change a student's retrieval pattern such that it is more efficient" (p. 318). In other words, "instruction does more than teach content. In addition, as a person learns new material, his cognitive structure is organized and modified in some way" (Loftus & Loftus, 1974, p. 318). This certainly fits in with the kinds of assertions that P. Johnson and Shavelson and colleagues were making, except that Loftus and Loftus see reaction time measure as a means of measuring cognitive structure changes, giving some insight into how concept organization changes as a function of learning. They conclude, "Reaction time measures such as the ones used in this study can give information about progress being made and ultimately about the

process of acquiring new material" (Loftus & Loftus, 1974, p. 318).

Two studies by Hambleton (Traub & Hambleton, 1974; Hambleton & Sheehan, 1977) are more closely aligned with the application of psychometric measurement methods in research on cognitive structure than was Loftus & Loftus, but the basic theme is the same as in their study. Traub & Hambleton (1974) investigated the effects of a course of instruction on students' structuring of concepts in statistics and psychometrics with the expectation that instruction will modify the way in which cognitive data are perceived, integrated, and organized. Like Shavelson and followers, they decided upon multidimensional scaling as a means of representing cognitive distances between concepts, and similarity judgments were used as the technique for gathering data by which to construct the similarity matrix. Effects of instruction were several. More reliable similarity judgments were produced, on the average, after instruction, although the reliability of individual students' judgments was generally fairly low (group data reliability coefficients were much higher); it is important to note here, however, that this is one of the only studies to report reliabilities. Instruction appeared to heighten students' perception of dissimilarities between concepts; and the dimensionality of the cognitive structure appeared to have been reduced from four dimensions previous to instruction to three dimensions following instruction.

Traub and Hambleton run into that old problem of interpretability, too, as they say that the dimensions of the configurations for cognitive structure did not readily present themselves in the results; only the post-course split between statistical properties and psychometric concepts was easily discernible.

Hambleton and Sheehan (1977) argue for using the match between instruction and students' cognitive organization of concepts as a basis for evaluating the effectivenss of instruction. The assumptions are again that instruction changes the structure of concepts in a person's head and brings it closer to either the content structure or the structure of an expert in that material. Hambleton and Sheehan use another type of analysis--that being latent partition analysis--of data gathered from similarity judgments and free-sort categorizations. The card sort task, it will be recalled, was not terribly successful in several of Shavelson's studies, but here it produced data well suited to a latent partition analysis (LPA).[6] The LPA assumes a hypothetical latent categorization of the concepts which underlies the sortings of individual subjects; its results, then, are in terms of categories into which concepts fall. Results in this study showed that categorization

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[6]Its success here might well be a function of the number of concepts given to subjects to sort; the number used on the Shavelson studies was probably too few.

did not change substantially as a function of instruction. Category adhesiveness increased and category confusions changed; the composition of categories for high achievers was somewhat different from that of low achievers, but what the changes indicate is difficult to tell. Hambleton and Sheehan's recommendations were that LPA solutions should be systematically compared before and after instruction, for high versus low achievers, for students receiving different instructional treatments, and for students versus the instructor or content expert. Finally, ways of obtaining and using "criterion" solutions should be sought.

The last study to investigate, using psychometric methodology, changes in cognitive structure accruing from instruction is Hess and Johnson (mimeo), a study which probably served as the forerunner to the Hambleton and Sheehan (1977) paper discussed above. Hess and Johnson use the sorting methodology and both latent partition analysis and multidimensional scaling to look at changes in students' conceptualization of physics concepts pre- and post-instruction in elementary physics. Their emphasis is on the usefulness of the methodology in illustrating cognitive structure changes and in ultimately aiding curriculum and instructional decision-making. In discussing the methodology, Hess and Johnson point out several of the pitfalls and shortcomings of the techniques and analyses that we have seen previous studies running into. "To derive a stable approximation to

the latent category structure of a group of subjects sorting fifty items may," for instance, "require a sample size of at least 100" (Hess and Johnson, mimeo, p. 13). That being the case, it is no wonder that Shavelson failed to produce useable results using the card-sort method; he had two subjects sorting seventeen concepts. In addition, "a lack of a priori dimensionality (i.e., attribute scales) along which items can be ordered tends to impose limitations upon the interpretability of category relatedness in an n-dimensional space. At best, all that can be done under such circumstances is to attempt to 'fit' axes in the space relative to the categories which would yield interpretable dimensionality" (Hess & Johnson, mimeo, p. 15). And, to date, this is what researchers have done in an effort to draw the most meaningful conclusions possible from their data. Finally, Hess and Johnson mention the same weakness of themethodology that has been noted here several times, namely that "at this time we have not developed adequate statistical procedures to determine the significance of differences in the overall relatedness of categories" (p. 19), which makes interpretations of structural change tentative at best.

Even being cognizant of the problems inherent in this methodology does not always insure that the study in which it is used will be a good one, as evidencedby Hess and Johnson (mimeo). They had college students enrolled in an elementary physics course sort physics concepts into cate-

gories both at the beginning and at the end of the semester, and the comparisons they made included not just pre- to post-instruction configuration changes but also comparisons between the configurations of low, moderate, and high achieving students, who were relegated to those respective groups on the basis of final grades. But, because no pre-test achievement measures were taken, Hess and Johnson have no way of relating what changes occurred in their structure measures to whatever learning took place over the course of the semester. They do, in fact, say that the differences in category cohesiveness gain scores among the three groups could be a function of pre-instruction differences. Changes in structural configurations and category cohesiveness did occur pre- to post-instruction, and differences were evident between the low, moderate, and high achievers, but, as always, Hess and Johnson preceeded all of their interpretations with "it might be" or "this could mean," etc. They conclude that what would add strength to their study and would be an important use of the methodology would be to analyze "differences between existing cognitive structure for a given curriculum area and a desired cognitive structure (i.e., some desired grouping of the concepts and terms or some desirable weighting of the dimensionality of the item space). Such an analysis should provide insights into the types of curricular experiences that might be needed to facilitate a reorganization of the total set or a subset of the

concepts and terms in a given subject matter area" (Hess & Johnson, mimeo, p. 45).

Psychometric Methodology for Measurement of Knowledge Structure

When attempting to judge the appropriateness of a particular methodology for investigating questions of interest in some field, there would appear to be two basic questions that deserve consideration: 1) will the procedures for collecting the data be consonant with the definition of the construct being assessed; in this case, for example, will the procedures being used tap the kind of structure that educators want to measure? and 2) will the model chosen for the analysis of the data provide interpretable solutions and allow reasonable conclusions to be drawn from its results? While the first question has been addressed to some degree, and at least implicitly, in the discussion of the studies purporting to measure content and cognitive structure and will be reconsidered at a later point, the second has not yet been taken up in any systematic way and therefore warrants attention.

The scaling methodology being extended to the measurement of knowledge structure grew out of the more general problem of measuring meaning. It has already been seen that the definition of meaning for the purposes of measurement has been adopted by those interested in representing content

and cognitive structure, and it will be seen to be reasonable and predictable for the measurement methodology to be adopted as well. As instruments were sought, then, for scaling relationships among concept meanings and recovering the dimensionality of semantic space, certain postulates came to be accepted. "For one thing, it is clear that it is a multidimensional space," claim Osgood, Suci, and Tannenbaum (1957, p. 71), referring to semantic space, and for another, it is affirmed that the meaning of a particular concept can be specified as a particular point in the multidimensional space defined by the scaling instrument (Osgood, 1969). According to Shepard (1960), the seemingly disparate notions of similarity and spatial proximity reduce to the same thing, so that a metric model becomes a convenient algorithm for describing semantic similarity. The semantic differential technique (Osgood et al., 1957; Osgood, 1969, Deese, 1965) was an initial approach to the investigation of relationships among words in a semantic domain by way of a rating-scale method. Persons are asked to judge the extent to which a concept can be described by a set of bipolar rating scales, and their ratings are factor-analyzed to represent the major dimensions along which meaningful judgments vary (Osgood and Suci, 1969). In generalizing from these procedures, researchers have moved toward collecting proximity data that can be subjected to multidimensional scaling routines. And proximity data, in the words

of Fillenbaum and Rapoport (1971), "include almost any measure of similarity, substitutability, cooccurrence, and association between every two stimulus objects or sets of stimulus objects (words, persons, groups, etc.) under study" (p. 9). But what about multidimensional scaling?

The purpose of multidimensional scaling is to get hold of whatever patterns or structure may be hidden in a matrix of proximity coefficients and represent that structure in a form more accessible to the eye (Shepard, 1972), i.e., a geometric picture. And "the primary purpose of such a representation is to enable the investigator to gain a better understanding of the total underlying pattern of interrelations in his data" (Shepard, 1972, p. 3). Subkoviak (1975) provides a good review of the three major lines of development in the computational methodology of multidimensional scaling (the Shepard-Kruskal, Tucker-Messick, and Carroll-Chang methods), particularly as they are applied in educational research, and the interested reader is referred to his paper for an analysis of the differences among the methods and their respective strengths and limitations. For the purposes of this discussion, it is important to note that the method applied in the studies reviewed was the Shepard-Kruskal method. This particular method makes no linearity assumptions about the function relating actual object proximities and distances recovered by the scaling routine, permits assumptions of either Euclidean or non-

Euclidean space, and produces few dimensions to facilitate representation and interpretation, thus making it especially suitable to data in a semantic domain.

Interpretability was cited as being a major problem in the studies using multidimensional techniques (criterial judgment of the results of any of the representational methods was shown to be a problem yet unresolved), and the definitional literature in multidimensional scaling shows procedures for interpretation to be in the early stages of development. Arriving at the correct dimensionality is a matter of choosing a representation for which the stress is not too large (i.e., the structure is a "good-fit" to the data; see Kruskal, 1964a, for the relationship between stress and goodness of fit), which is readily interpretable and which is easily visualizable. Once the number of dimensions has been selected, "some analysts have stressed the interpretation [of the representation] in terms of naming and labelling dimensions, while others impose a less restricted interpretation and speak only in terms of regions in which objects in the same region are interpreted as being similar" (Nerlove and Romney, 1972). Subkoviak's (1975) advice is to avoid becoming enamored of labels on dimensions and to consider alternative methods of analyzing the data if no reasonable interpretations surface. In any event, the final interpretation of the representation--in terms of the appropriate number of dimensions and their possible labels--

"rests ultimately with the scientific judgment of the experimenter" (Kruskal, 1964a, p. 15).

While the interpretability of multidimensional scaling solutions may not be as refined as we could want, the technique still appears to have potential for use in the investigation of problems in the social sciences in general and cognition in particular. Besides its application in the studies earlier reviewed, Stefflre (1972) has found it a useful descriptive tool for studying regularities in the patterns of behavior of aggregates; Wexler and Romney (1972) found it helpful in characterizing the similarity structure of kinship terms; and Michon (1972) has used it to demonstrate growth and differentiation during the learning of complex data structures. He further suggests that "such models could possibly show such effects as the trade-off between acquisition of data and stability of the internal representation, or deformation caused by natural forgetting, or provide insight in the process of interiorization" (Michon, 1972, p. 115), an application very much in line with the aims of the educational researchers looking to use measures of cognitive structure as ways of evaluating learning. Finally, Subkoviak (1975) concludes that "multidimensional scaling has reached a state of development such that the educational researchers should seriously consider adding it to his repertoire of research tools" (p. 418).

While at a lesser stage in development as multidimen-

sional scaling routines, categorization methodology (Miller, Wiley, Wolfe and Conry, 1969) is nonetheless being explored as another way of tapping cognitive structure. Sorting techniques used here as means of collecting categorical data, and latent partition analysis (LPA) is used to reduce the data to interpretable categories assumed to be manifestations of latent relationships within cognitive structure. A major criticism aimed at this approach is that since randomness is its central feature, its status as a psychological model is questionable (Wolfe, mimeo). Perhaps because of that or because the analysis, to be reliable, depends upon a large number of sorters sorting the chosen key concepts, this methodology has not found as wide an application in educational areas as multidimensional scaling.

Finally, although S. Johnson's (1967) hierarchical clustering technique and Waern's (1972) graphic analysis, both discussed earlier, have as yet received no further mention, they are also techniques for representing structure that operate on proximity data. As seems patently obvious, Johnson's analysis is most appropriate with clearly hierarchical relationships between concepts, while Waern's method may be more useful when the structural nature of conceptual relationships is not evident a priori. Waern's analysis has the disadvantage, though, of depicting connective relationships at the expense of the degree of association in the relationships. Both of these, however, would appear to have

their uses, and all of these psychometric methods have some amount of potential for depicting structure in ways that may facilitate the educator's task of evaluating learning of subject-matter structure.

Summary and Implications

Despite the growing number of applications of this scaling methodology to the measurement of knowledge structure and the attempts of Shavelson to validate the experimental techniques used to assess structure, some question remains as to whether, in fact, these methods tap the aspects of structure related to comprehension and subsequent learning on the level that we, as educators, generally want to measure. Although measures of word association and concept relatedness have long been accepted as good indicators of conceptual structure--and, indeed, Johnson expended a great deal of effort to establish that--there is at least one study that throws some doubt on their utility in the evaluation of learning of subject-matter structure. Rothkopf and Thurner (1970) taught the same physics material as Johnson had used to a group of volunteer high school students for the purpose of determining whether the students' verbal outputs involving key physics concepts would be affected by word distributions and conceptual structure in the material. Before and after instruction, they administered achievement tests to assess overall learning of the

material and both word-association and prompted essay[7] tests to measure verbal output. Their results showed that while neither text frequency distributions nor those of any group of students on either the WA or essay measures correlated very highly with the frequencies of key words in the Thorndike-Lorge general count or the Klaus-Andres count in technical instruction, the frequency distributions of only the experimental[8] group of students <u>after</u> instruction increased in resemblance to the frequency distribution of the textual material. At first glance, this result would appear to support the notion that association measures can assess learning of structure, but the catch is that no achievement gains were demonstrated in this study. The comparison of gain scores between the control and experimental group showed that they were not significantly different, i.e., the experimental group receiving the instruction did not learn the concepts as measured by the traditional achievement test. Since it appears as though students began to write like physics textbook writers before showing signs of other relevant intellectual skills, Rothkopf and Thurner conclude that "the use of word-association procedures to evaluate

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[7]Students were instructed to write all they knew about the key concepts, printed one to a page in the test booklet, and they were given three minutes writing time for each.

[8]The experimental group received the relevant physics instruction, while the control group received unrelated instruction.

academic achievement should be approached with caution" (1970, p. 88).

It could be the case, therefore, that the level of structure that is being assessed by these various measures of concept interrelatedness is one that is learnable by rote with no real comprehension of the material required. If that were true, cognitive structure might appear to approximate content structure while recall or some other indication of achievement remained low, as happened in Rothkopf and Thurner (1970). If, on the other hand, these measures do tap appropriate structure, then they should be able to discriminate among students in different states of learning after equivalent instruction (an indication of the validity of the techniques, which Shavelson has not indisputably established). The degree to which student cognitive structures match content structure, in other words, should parallel the extent to which those same students can meaningfully recall the information taught.

Accepting, for the moment, the supposition that these testing methods can, in fact, access structure at the level of comprehension, not just rote memorization, of concept relatedness, another potential use for the methodology arises with respect to evaluating a learning effect termed nonspecific facilitative transfer by Royer and his associates (Royer and Cable, 1975, 1976; Royer and Perkins, in press). In their studies, students learned more from a difficult

abstract passage when they had first encountered a related, concrete passage, which was designed to act as a "knowledge bridge" between what they already knew and the difficult material they were asked to learn (Royer & Cable, 1975). While Royer and Cable (1976) showed that the "style" of the passages does not account for the facilitative effect, what actually does transfer (in structure, perhaps) from the first to the second passage to explain the effect is not clear. Applying these psychometric methods for representing structure to thissituation might, therefore, give us a handle on what nonspecific transfer actually is.

Problem

The purposes of this study, then, are twofold. First, it proposes to investigate the question of whether the psychometric methods and models applied to the measurement of cognitive structure actually extract information about structure that would be valuable to educators. Are they, indeed, sensitive to differences in comprehension that lead to differences in amount and substance of recall or achievement? If so, they may become valuable tools for the assessment of learning and failures to learn. Or do they, rather, disclose a structure of relationships that can be learned without true comprehension of the material on the part of the student? In that case, students receiving similar instruction should display similar cognitive structures

regardless of the differences that might exist among them in actual understanding of the material.

The second aim of the study involves an attempt tc find a more complete explanation of the facilitative learning effect shown by Royer _et al_. than has been offered by applying the psychometric methodology to their learning conditions. Using their materials also serves the dual purpose of validating the methodology, since they have created a situation in which the learning of students in different treatment groups is demonstrably different. Parallel differences between these groups appearing on analyses of word-association and graph construction measures would lend credence to the claim for their validity.

The study consists of 5 treatment groups, presented in Table 1, which may be conceived of as a 3 x 2 factorial design (type of first passage--facilitative/concrete, non-facilitative/abstract, structure-training--by instructions to underline, or not, key concepts) with one cell missing: the underlining variable is not crossed with the structure-training condition. All groups will receive the same second passage.

Table 1: Design

	Groups	
Facilitative 1st Passage		
Underlining	HC-EA/U*	(1)
No Underlining	HC-EA	(2)
Nonfacilitative 1st Passage		
Underlining	HA-EA/U	(3)
No Underlining	HA-EA	(4)
Structure-Training 1st Passage	ST-EA	(5)

*H=Heat Flow, E=Electrical Conductivity
A=Abstract, C=Concrete, ST=Structure-Training

The predictions for the study are:

1) Subjects in the facilitative 1st passage conditions (Groups 1 and 2) should recall more than subjects in the nonfacilitative 1st passage conditions (Groups 3 and 4). Underlining should have little effect on recall.

2) If the WA and GC tests measure structure that depends upon comprehension, then underlining will have no effect on cognitive structure, and the EA cognitive structures of those in the facilitative 1st passage conditions (Groups 1 and 2) will more closely approximate the EA content structure than that of the students in the non-facilitative 1st passage conditions (Groups 3 and 4). Three other predictions conditional upon this comprehension-structure link are: (a) HC cognitive structures should

approach the HC content structure since the HC passage is easily understandable without prior information; (b) HA cognitive structures will not be similar to the HA content structure since the content in HA is difficult to comprehend without benefit of prior knowledge; and (c) recall of the ST group (5) should be facilitated compared to the nonfacilitative 1st passage conditions, with the EA cognitive structure of this group approximating the EA content structure.

3) If the WA and GC test measure a superficial level of structure, not dependent upon comprehension, then the cognitive structures of those who underlined (Groups 1 and 3) should more closely approximate their respective content structures than those subjects who did not underline (Groups 2 and 4). Also, conditional upon this state of affairs are the following two predictions: (a) the EA cognitive structures of the ST group will be similar to the EA content structure but their recall scores will be low, and (b) no differences in structure will be observed for the groups that did not underline.

CHAPTER II

METHOD

Subjects: One hundred and seven students at the University of Massachusetts participated in the study during the spring and summer semesters. Most of these students were enrolled in spring and summer session psychology courses and received experimental credit for their voluntary participation. A few who volunteered during the summer were either recent graduates of the University or were students enrolled in summer courses offered by other departments; these students were not recompensed in any way for their participation.

Students were randomly assigned to the five treatment groups. Because a few students failed to finish the task or did not follow directions, additional subjects were run to replace them. The final distribution of subjects per treatment group is displayed in Table 2.

Table 2

Distribution of Students in Experimental Groups

TREATMENT	(GROUP)	# of SUBJECTS
HC-EA/U*	(1)	20
HC-EA	(2)	20
HA-EA/U	(3)	20
HA-EA	(4)	20
ST-EA	(5)	21

*HC = Heat Concrete
HA = Heat Abstract
EA = Electrical Abstract
ST = Structure Training
U = Underlining required

Materials: The materials used in the study consisted of three different instructional passages--heat flow (H), electrical conductivity (E), and structure training (ST)--a word association (WA) test, and a graphic construction (GC) test, each of which is described below. Samples of all materials--passages and tests--can be found in Appendix A.

H and E passages. The two versions, concrete (C) and abstract (A), of Royer and Cable's (1975) heat flow passage were used as the first passage in experimental groups one through four (see Table 2), and the abstract version of their electrical conductivity passage was used as the second passage in all groups. For a specific description of how these passages were generated, see Royer and Cable (1975). Briefly, though, the composition of the heat and electrical passage is similar; each begins with a segment describing the specific phenomenon (H or E), followed by a section describing the structure of metals and a final section discussing factors which affect the respective phenomena. The concrete versions of each passage provide concrete referents for the new concepts introduced so that they are easy to understand in and of themselves. The abstract versions, on the other hand, lack these referents and are therefore difficult to understand without benefit of a prior knowledge structure by which to organize the information presented. Since passage order had been counterbalanced in previous studies with no resultant interaction with treatment effect,

counterbalancing was felt to be superfluous here. The H-E order was chosen simply because the facilitative effect achieved previously with that sequence had been slightly, though not significantly, stronger than with the reverse, E-H, order.

Structure-training passage, word-association tests, and graphic construction tests. Graduate student judges independently read the H and E passages with instructions to list what they thought were the key concepts in the material. On the basis of their judgments, 16 key concepts were selected for the two versions of the H passage and 13 key concepts were selected for the E passage; both sets of concepts are listed in Table 3.

Table 3
Key concepts selected for the heat flow and electrical conductivity passages

Heat Flow:	heat flow	agitation velocity
	conduction	collisions
	metal	pressure
	structural regularity	impurities
	transfer of motion	temperature
	electrons	distortion
	bonded molecules	transmission
	crystal lattice	thermal agitation
Electrical Conductivity:		
	conductor	atomic structure
	current flow	collisions
	pole	conductive efficiency
	metal	thermal state

(Table 3 continued)

electron	magnetic force field
structural regularity	agitation velocity
crystal lattice	

The structure-training (ST) passage used as the initial passage in experimental group 5 was constructed on the basis of a content structure analysis of concept interrelationships performed in the abstract electrical passage. The procedure by which passages may be analyzed for content structure is fully described in a later section entitled "Representation of Content Structure," so for the purposes of this section, only the results of the analysis for the EA passage need be presented. First, the relationships of each of the 13 key concepts for the E passage (listed on Table 3) to every other concept in the list, in the form of similarity coefficients, were summarized in a similarity matrix. Then, upon submitting this matrix to both multidimensional scaling (Kruskal, 1964a, b) and graphic representation (Waern, 1972) analyses, two representations of structure were obtained and combined to produce one, two-dimensional picture of key concept interrelatedness. And the ST passage was constructed around this picture for the purpose of training subjects to reproduce the relationships when given an identical list of concepts. The actual composition of the passage, therefore, was as follows. An opening paragraph stated the purpose of the passage, listed the key concepts, and instructed the

reader to study the diagram. A middle section described how the diagram should be interpreted and presented all of the concept relations that could be gleaned from the picture. And a summary section re-presented the diagram for review. The overall length of the ST passage was approximately the same as the H and E passages.

The word-association and graphic construction tests were also constructed from the lists of key concepts presented in Table 3. Each WA test was a booklet comprised of a page of instructions followed by the key concepts for the passage being tested, printed one to a page and randomly ordered. Below each concept were printed two columns of lines, on which subjects were to write their responses. Each GC test consisted of an envelope containing key concepts printed on self-adhesive labels attached to a page of instructions and a blank sheet of paper. The blank sheet of paper served as the response sheet on which subjects were to stick the labels in patterns depicting their cognitive representations of interconcept relations.

<u>Procedure</u>: The experiment took place over two sessions, on two successive days, with each session running approximately 45 minutes. Subjects were tested in groups ranging in size from one to twenty-five, and all were run in a standard classroom. In the first session, subjects were handed a booklet containing, in this order: 1) a set of general

instructions explaining the general nature of the study and summarizing the procedure of both experimental sessions, 2) a set of specific instructions directing them to either read the succeeding passage slowly and carefully twice, or to read the passage slowly and carefully once and upon reading it a second time, to underline the key concepts in the material, and 3) the first passage (HA, HC, or ST). Subjects were given 15 minutes to complete their reading of the first passage, and all subjects finished well within that time limit. Booklets were then collected and the WA tests administered. Students had one minute per page of the WA test to write down as many words or concepts as they could think of that related to the word or phrase printed at the top of each page. They were instructed to glance frequently at the word to which they were responding to be sure that their responses were directly related to it and not to some previous response, but they were not restricted to associations that could only be garnered from the passage they had just read. After completion of the WA test, students were given unlimited time to depict, on the GC test, the structure that best represented concept interrelationships as they understood them from the passage they had just read. In order to do this, they were instructed to move the labels around on the blank sheet of paper until they felt they had the best representation of what they understood and remembered. Having decided upon a particular configuration, they

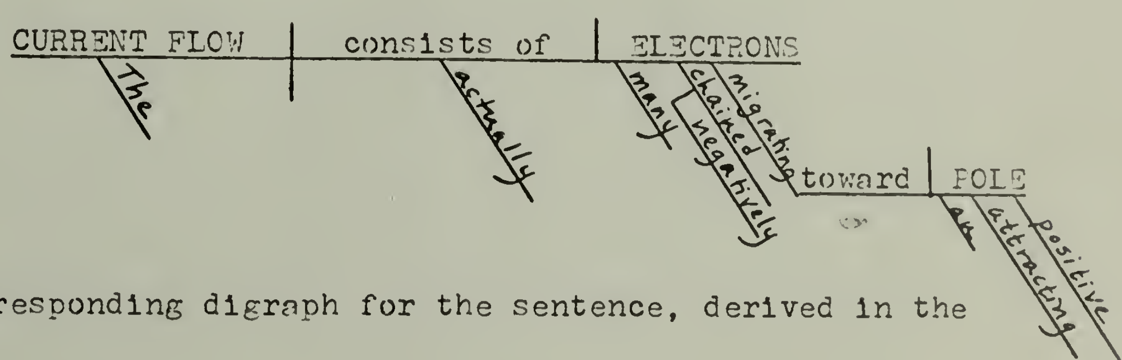
were to peel off the backs of the labels, affix them in position, and draw lines between interconnecting concepts.

The second session was conducted in a similar fashion to the first. Booklets containing the second passage (EA) and a set of instructions were distributed and subjects were given two minutes to read each of the three pages of the passage. They were told not to move ahead without being directed to do so and not to turn back to any previous page; they were allowed, however, to look back at sections of the page they were on if time permitted. Immediately following their reading of the second passage, subjects were given a free recall test, for which they were instructed to write down as much as they could remember from the passage they had just finished reading (the second passage). They were told that full sentences were not necessary, nor should they worry about spelling or grammatical errors; what was important was that they write down as many complete ideas as they remembered. Students were given approximately seven minutes for this task, a time which was judged from previous studies to be more than adequate. Only a few subjects required, and were allowed, more time. When free recall protocols were collected, the WA and GC tests on the second passage were administered in the same manner as for the first passage.

Students were allowed to ask questions at any time during the experiment, and a short debriefing period followed the second session.

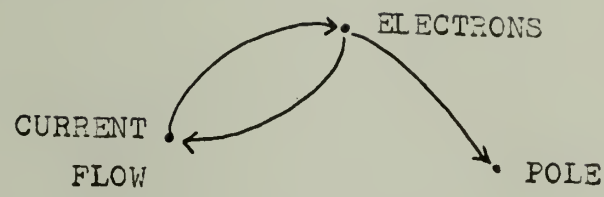
Scoring and Analysis

Representation of Content Structure. The content structure of all three passages--EA, HC, and HA--was obtained through a series of analysis steps established by Shavelson and his associates. Accordingly, every sentence in each passage which contained two or more of the key concepts identified for the respective passage (see Table 3 for the list of concepts) was first diagrammed according to a standard parsing grammar (Warriner & Griffiths, 1957). The second step in the process involved converting these sentence diagrams to sentence digraphs using Shavelson and Geeslin's (1975) conversion rules, digraphs which formed the basis for a concept distance matrix (Harary, Norman, and Cartwright, 1965) for the passage under analysis. To exemplify the analysis process so far, consider the following sentence from the abstract electrical passage: "The current flow actually consists of many negatively charged electrons migrating toward an attracting positive pole" (key concepts are underlined). In the first step, the sentence would be diagrammed as:



The corresponding digraph for the sentence, derived in the

second step, would be as follows.



A symmetric relationship between CURRENT FLOW and ELECTRONS is shown because of the definitional nature of the verb, and the asymmetric relationship between ELECTRONS and POLE reflects the directional nature of "migrating toward." Combining all the individual sentence digraphs into one super-digraph and corresponding distance matrix constituted the third step in the analysis. The distance between any two concepts, which is an entry in the distance matrix, is represented by the number of lines in the shortest path between the two concept points, and the distance matrix is merely a summary of the distances between every key concept and every other key concept. The final step of analysis prior to submitting the data to statistical scaling techniques was to convert the distance matrix to a similarity matrix using the transformation: $y = 1/(x + 1)$ (Geeslin & Shavelson, 1975). Now, the entries in the matrix indicate the "closeness," or interrelationship, of each pair of concepts, rather than the distance between them.

Once the similarity matrices were obtained, the data was submitted to a multidimensional scaling routine (Kruskal, 1964a, b), and a graphic representation routine (Waern, 1972)

in order to recover the underlying relational structure of the concepts.[1]

Representation of Cognitive Structure. All three measures of learning outcomes used in this study tap some aspect of cognitive structure as it has been defined. The relevant questions were whether the representations resulting from the GC and WA tests were similar to each other, whether these representations resembled the appropriate content structures, whether these representations were sensitive to learning differences brought about by treatment conditions, and just what the relationship was between the GC and WA measures and the more conventional free recall. In order to have even considered some of these questions, however, measurements taken with these methods must have been congruent to measurements of content structure and appropriate to the same kinds of analyses used on content structure.

Word association tests. For each test, the dependent variable of greatest interest was the overlap of responses for pairs of stimulus words. While measures such as the total number of responses to each stimulus word, the average number of responses to each word, and the number of responses of a particular type to each word may be useful to some degree, it has generally been agreed (Shavelson, 1974)

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[1]Multidimensional scaling and hierarchical clustering (S. C. Johnson, 1967) analyses have been used to yield spatial and rooted hierarchical representations structure,

that the information available from the overlap in response lists to pairs of words is most consistent with cognitive structure as it has been defined here. Using Garskoff and Houston's (1963) relatedness coefficient as a proximity index, then, similarity matrices of first and second passage WA test results were produced for each subject. These matrices were then subjected to the same analyses used upon the content structure matrices.

Graphic construction tests. Interconcept proximity matrices were also obtained for subjects on first and second passages from the graphs they produced on the GC tests. These matrices were based upon the number of links between pairs of key concepts in the structures produced by subjects, distances which were converted to similarities by the same transformation used in the analysis of content structure. Matrices produced here were, again, analyzed in the same routines as for WA and content structure matrices.

Free recall. Recall protocols were scored according to the technique developed by Royer and Cable (1975). Royer and Cable subjectively parsed the heat and electricity passages into idea units and then scored subject protocols for

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respectively, when it has been suspected *a priori* that the underlying structure may be dimensional/spatial or hierarchical. When there are no grounds upon which to make *a priori* assumptions about structure, Waern's (1972) technique of graphic representation has been used and justified (Preece, 1976; Rudnitsky & Garlock, 1977).

the presence of these units. Interscorer reliabilities have typically been very high, never less than .90, and the scores obtained represent the proportion of ideas recalled from the passages. In this study, recall was required only for the electrical-abstract passage, which contained a total of 52 idea units.

CHAPTER III

RESULTS

Recall

The number of idea units recalled by individual students in all treatment groups can be found in Appendix C; summarized in Table 4 are the mean numbers of idea units recalled as a function of treatment, as well as the respective standard deviations for each group.

Table 4

Mean number of idea units recalled by students according to treatment groups

TREATMENT	(GROUP)	MEAN	S.D.
HC-EA/U	(1)	10.00	3.60
HC-EA	(2)	9.20	3.30
HA-EA/U	(3)	6.10	2.88
HA-EA	(4)	8.75	3.89
ST-EA	(5)	7.33	2.82

An overall analysis performed on the recall data included all five treatment groups in a one-way analysis of variance for independent groups. The score of one subject was randomly dropped from group 5 in order to achieve an equal number of students per group. Results of this analysis are summarized in Table 5 and reveal a significant main effect for the type of first passage read by the students on their recall of the second passage.

Table 5

Analysis of variance comparison of type of first passage on idea unit recall of the 2nd passage

Source of Variance	df	MS	F	p
A (type of passage)	4	50.24	4.58	<.01
S/A	95	10.98		

Because of the specific predictions made concerning possible effects of the type of first passage received and instructions to underline or not, and because of the analysis results indicating significant differences among treatment groups, multiple planned comparisons seemed warranted to uncover the precise nature of the differences. The specific questions of interest included a) whether the concrete first passage groups (1 and 2) recalled more than the abstract first passage groups (3 and 4), b) how the recall of the structure-training first passage group (5) related to the other four, and c) how instructions to underline interacted with the type of first passage received. These resulted in five non-orthogonal comparisons, each tested at a significance level of .01. According to Myers (1972), performing five planned comparisons testing each at a significance level of .01 would result in a .05 experiment-wise error rate, even for nonorthogonal comparisons. "It can be proven from elementary probability theory that the probability of at least one type I error for a set of k nonindependent tests, each carried out at the EW/k level, is less than EW.

Therefore, we recommend the procedures described above for the orthogonal case, even when the contents are not orthogonal" (Myers, 1972, p. 362).

Results of the calculated comparisons indicated first that recall of the concrete initial passage groups (combined) significantly exceeded that of both the abstract first passage groups (combined) and the structure-training first passage group (t[1] $= 9.73$, $p < .01$ and $t = 8.95$, $p < .01$, respectively); there proved to be no difference between recall of the structure-training group and that of the combined abstract first passage groups ($t = 1.00$, ns). Concerning the effects of underlining on recall, the group receiving an abstract initial passage but <u>not</u> told to underline recalled significantly more idea units than the abstract first passage group instructed to underline ($t = 8.38$, $p < .01$). This effect was reversed in the groups receiving the concrete initial passage, but only approached significance at the .01 level: the group with instructions to underline performed better than the group without those instructions ($t = 2.52$, .01 $p < .025$). The interactional effect indicated here of the type of first passage by instructions to underline or not was also confirmed by a 2 x 2 ANOVA performed on the recall data of groups 1 through 4 ($F_{1, 76} = 16.53$, $p < .01$).

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[1]Bonferroni t statistic; critical values are presented in Table A-12 of Myers (1972).

Content Structure

Electrical Passage. Waern's (1972) multistep method of graphic analysis was applied to the electrical passage similarity matrix obtained through the digraph analysis of the passage content, and the resulting representation of concept interconnectedness is displayed in Figure 1. The concept abbreviations, along with the concepts for which they stand are as follows:

CD = Conductor
CF = Current Flow
ME = Metal
SR = Structural Regularity
AS = Atomic Structure
CL = Crystal Lattice
MFF = Magnetic Force Field
PO = Pole
EL = Electrons
CO = Collisions
CE = Conductive Efficiency
AV = Agitation Velocity
TS = Thermal State

Concepts connected by solid lines were more highly associated (coefficients > .40) than those connected by dashed lines (coefficients between .20 and .40). This representation, combined with the two-space multidimensional scaling solution (stress = .21) obtained for the structure of the same set of concepts (portrayed in Figure 2), formed the basis for the diagram used in the structure-training passage.

Following the Kruskal (1964a) and Shepard (1972) criterion for selecting the most appropriate number of dimensions for a particular representation, i.e., basing the selection on the "elbow" in the stress vs. dimension curve,

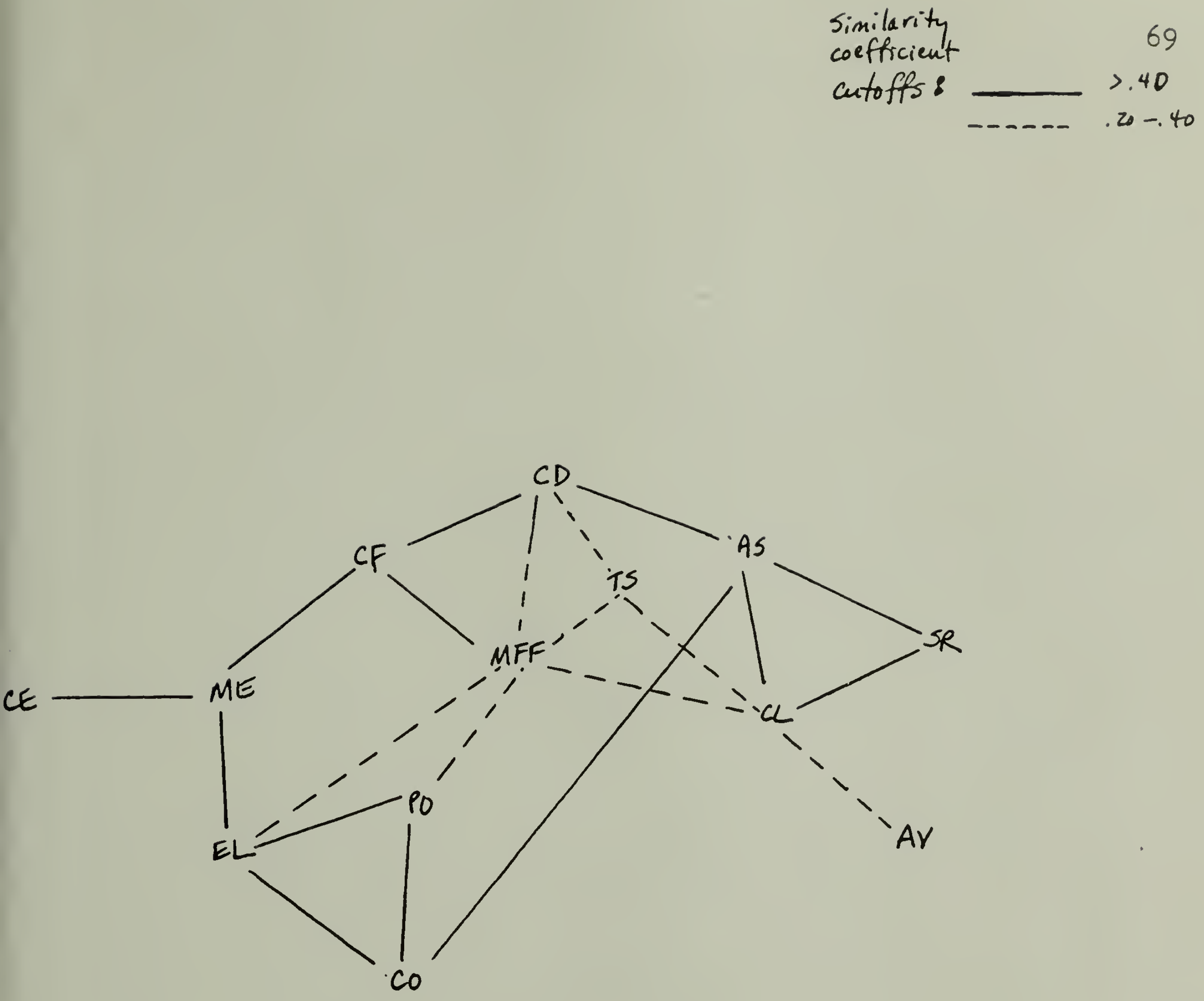

Figure 1: Graphic solution (Waern, 1972) for the content structure of the electrical concepts (abstract).

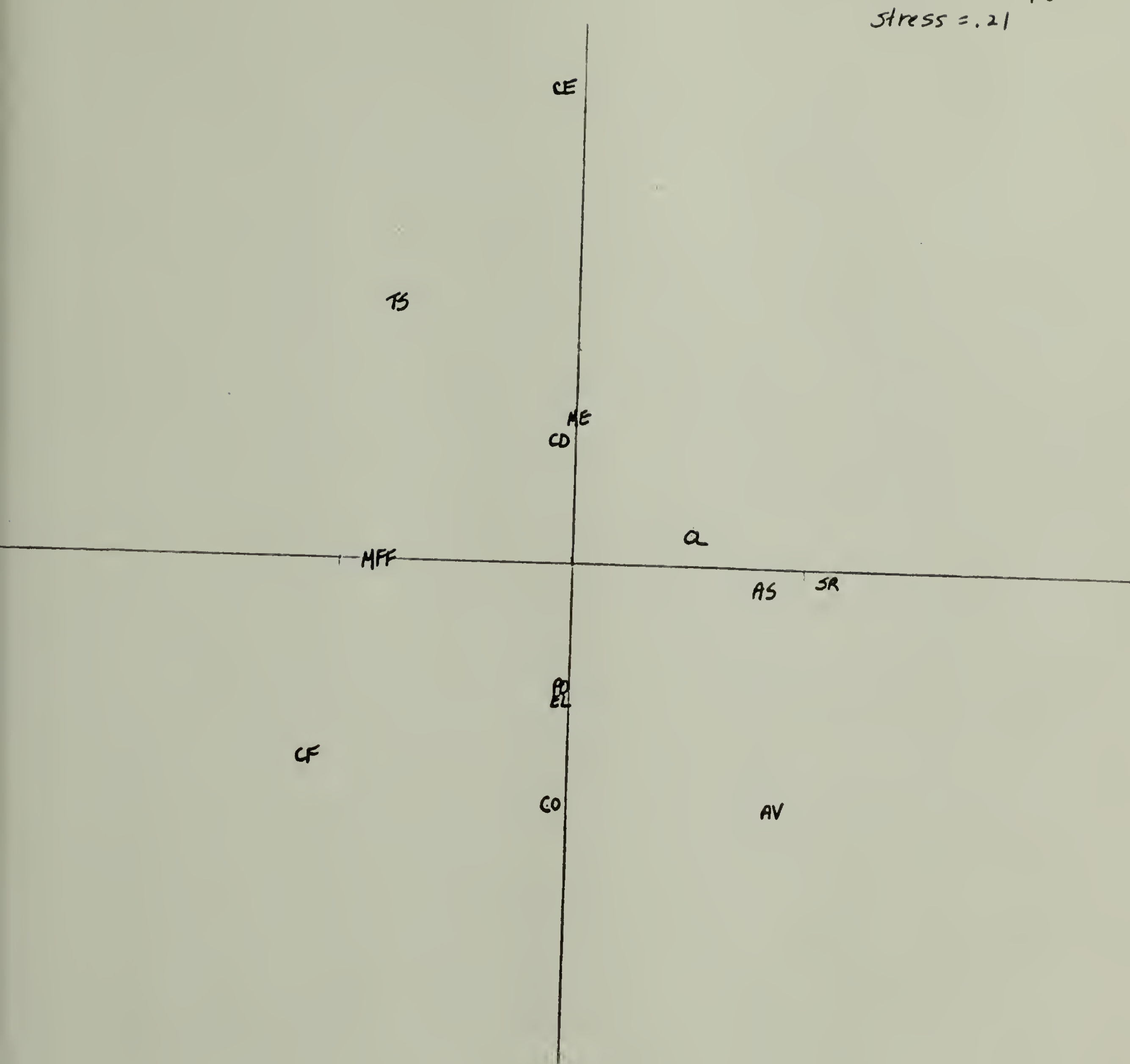

Figure 2: Multidimensional scaling solution — two space configuration for the content structure of the electrical concepts (abstract).

the correct number of dimensions for the electrical passage content structure was three (3). (See Figure B-1, Appendix B, for a plot of stress as a function of dimension for the electrical content structure.) For the purposes of training structure, however, stress was sacrificed for visualizability and the two-dimensional representation was selected. Results indicated four concepts aligned on one dimension (MAGNETIC FORCE FIELD, CRYSTAL LATTICE, ATOMIC STRUCTURE, and STRUCTURAL REGULARITY) and six along the other (CONDUCTIVE EFFICIENCY, METAL, CONDUCTOR, POLE, ELECTRON, and COLLISIONS). THERMAL STATE, AGITATION VELOCITY, and CURRENT FLOW did not appear to readily align with either dimension. Comparing this representation (Figure 2) to the graphic solution presented in Figure 1, at least two similarities were apparent. As in the scaling solution, ATOMIC STRUCTURE, CRYSTAL LATTICE and STRUCTURAL REGULARITY were strongly interassociated in the graphic solution and CONDUCTIVE EFFICIENCY, METAL, ELECTRON, POLE, and COLLISIONS formed a strongly associated chain, with the latter three concepts being interconnected.

Heat passages. Two-space configurations for the heat concrete and the heat abstract content structures were obtained using the Shepard-Kruskal method, and both had lower stress values (.14 and .12, respectively) than the two-space solution for the electrical content structure. Again, although a two-dimensional solution was easier to

visualize, three dimensions were indicated as being more appropriate for the heat concrete structure (see Figure B-2, Appendix B). No "elbow" was apparent in the stress vs. dimension curve for the heat abstract structure (see Figure B-3, Appendix B); two or three dimensions seemed equally <u>a propos</u> by that criterion. More recent discussions of how to interpret stress values, however, have indicated that distinctive "elbows" appear only in reasonably error-free data and that stress-percentages are dependent upon the number of stimuli involved (Klahr, 1969; Wagenaar and Padmos, 1971). The process of determining both the presence and true dimensionality of structures, then, has become one of comparing the stress functions of the data in question to functions of randomly generated structures (Stenson and Knoll, 1969; Klahr, 1969; Wagenaar, 1971). If the empirical values of stress are too close to the stress values for random data, then the chosen number of dimensions may not be appropriate. According to the maximum values of stress that can be accepted for a significant structure involving n points in m dimensions, as follows,

m =	1	2	3	4	
n = 12	.40	.21	.10	.07	(Wagenaar & Padmos, 1971)
n = 12	.45	.24	.14	.09	(Klahr, 1969)
n = 16	.48	.28	.19	.14	(Klahr, 1969)

The empirical values found here indicate the presence of

significant structure that might well be represented by two or three dimensions. The two-dimensional scaling solutions for the heat concrete and abstract passages, therefore, are displayed in Figures 3 and 4, respectively, and the relevant concept abbreviations are as follows:

HF = Heat Flow	AV = Agitation Velocity
CD = Conductivity	CO = Collisions
ME = Metal	PR = Pressure
SR = Structural Regularity	IMP = Impurities
TM = Transfer of Motion	TEM = Temperature
EL = Electrons	DIS = Distortion
BM = Bonded Molecules	TR = Transmission
CL = Crystal Lattice	TA = Thermal Agitation

Although not as clearly evident as in the electrical content structure, the two dimensions for the heat concrete structure appeared to be comprised of a concept dimension including DISTORTION, BONDED MOLECULES, COLLISIONS, STRUCTURAL REGULARITY, IMPURITIES, and PRESSURE and one involving CONDUCTIVITY, HEAT FLOW, METAL, TEMPERATURE, and the cluster ELECTRONS-THERMAL AGITATION-CRYSTAL LATTICE. TRANSMISSION and AGITATION VELOCITY formed their own small cluster, more closely associated with the second group listed than the first, and TRANSFER OF MOTION appeared about as closely associated to one dimension as the other.

The two dimensions falling out of the solution for the heat abstract structure seemed to be one involving TRANSFER OF MOTION, HEAT FLOW, STRUCTURAL REGULARITY, COLLISION,

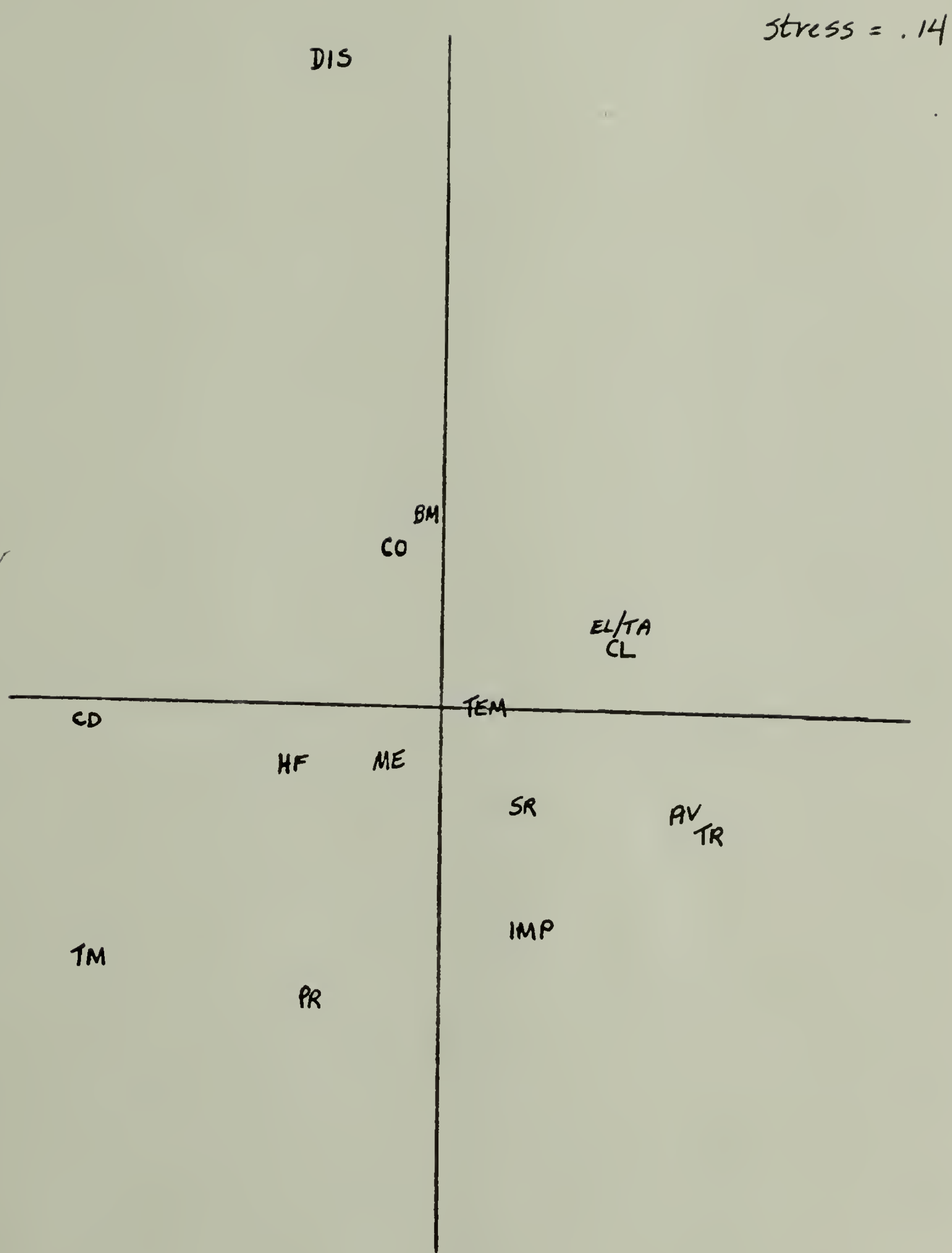

Figure 3: Multidimensional scaling solution — two space configuration for the content structure of the heat flow concepts (concrete).

Stress = .12

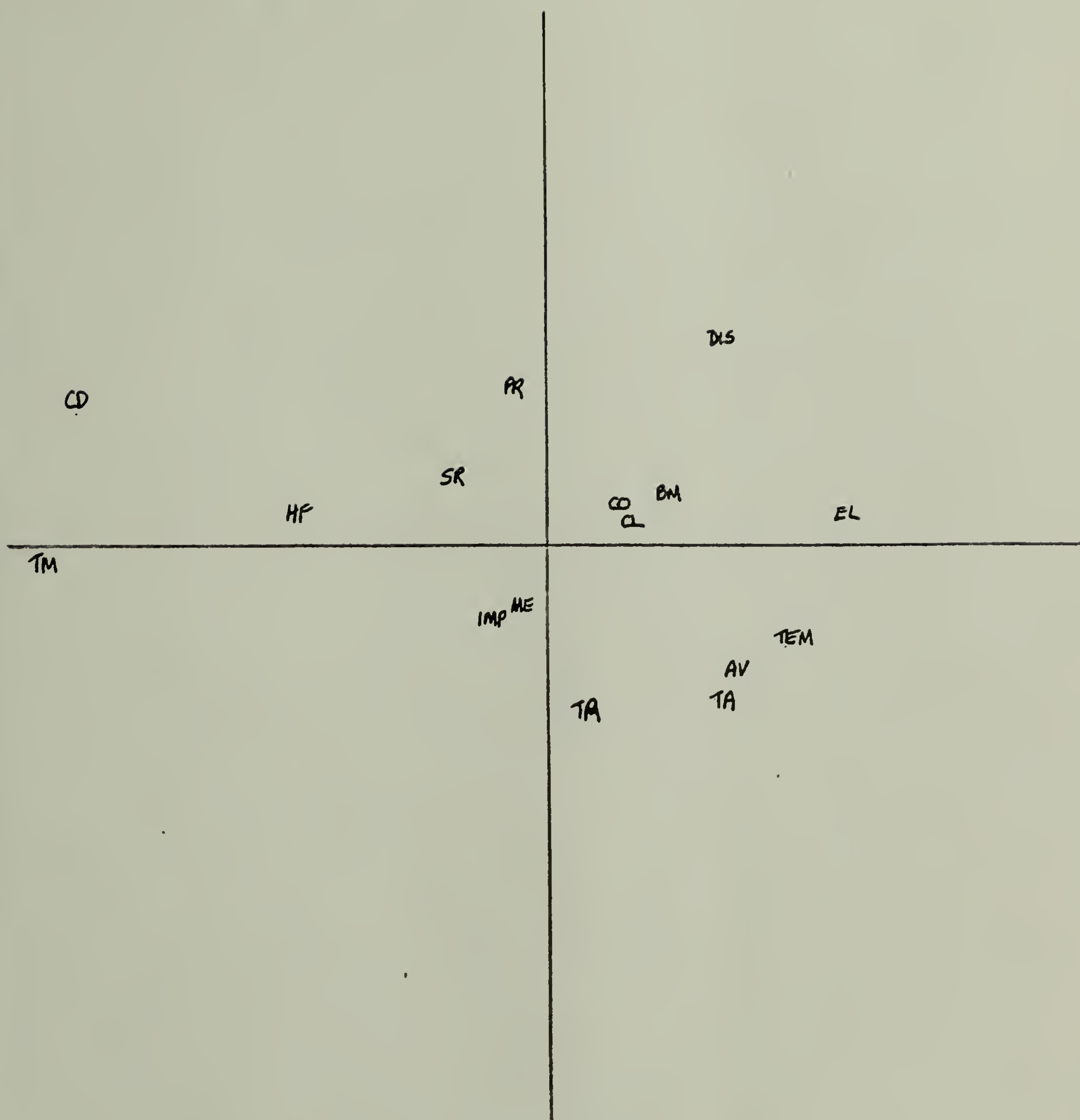

Figure 4: Multidimensional scaling solution — two space configuration for the content structure of the heat flow concepts (abstract).

CRYSTAL LATTICE, BONDED MOLECULE, and ELECTRON and the other including PRESSURE, STRUCTURAL REGULARITY, METAL, IMPURITIES, and TRANSMISSION. One additional small cluster appeared, comprised of TEMPERATURE, THERMAL AGITATION, and AGITATION VELOCITY, and both CONDUCTIVITY and DISTORTION seemed to be somewhat remote from any other concepts, although the former is probably more associated with the first set of concepts listed than with the second.

A basis for comparison among all three content structures is the set of concepts that the electrical and heat passages have in common, namely CONDUCTOR/CONDUCTIVITY, METAL, STRUCTURAL REGULARITY, CRYSTAL LATTICE, COLLISIONS, ELECTRONS, AGITATION VELOCITY, and ATOMIC STRUCTURE/BONDED MOLECULES. In the electrical passage, which was the passage of interest in terms of amount learned, CD, ME, EL, and CO were ordered together, and CL, SR, and AS were ordered together, with AV standing alone. Notice the similarity between that structure and the structure of the heat concrete passage, in which CD, ME, EL, and CL were ranked together, and SR, BM, and CO were ordered together, with AV remaining isolated. In the heat abstract passage, on the other hand, both CD and AV remained apart from the other critical concepts, while SR and ME appeared in one group, and SR, CO, CL, BM, and EL were ordered in another. When it comes to interpreting the facilitative effect of the heat concrete passage, but <u>not</u> of the heat abstract passage, on electrical passage learning,

these structural similarities and differences will figure prominently.

Cognitive Structure

Multidimensional scaling solutions were obtained for the cognitive structures, as measured by the GC and WA tests, of each of the five treatment groups and of both the first and second passages read. In other words, twenty configurations of cognitive structure were obtained from matrices averaged over individual subject data: five treatment groups x two tests administered to each group x two passages read by each group. The stress functions for all solutions are presented in Appendix B (FiguresB-4 through B-23), along with the two-dimensional configurations found for each structure and depicted automatically by the scaling routine (Figures B-27 through B-46). A summary of recommended dimensions for each cognitive structure solution, based on the Shepard-Kruskal criteria, is presented in Table 6. In all cases, overall stress was considerably higher than was found in the content structure solutions (ranging from .22 to .60 for two-space solutions and from .14 to .26 for three-space solutions) and was most likely a function of additional "noise" in the data. Recommended dimensions here should also be approached with caution, since few of the stress values for these solutions were low enough on Wagenaar and Padmos' (1971) and Klahr's (1969) scales to indicate

structure significantly different from that which could be produced from random data.

Table 6

Recommended dimensions for the cognitive structure solutions obtained from each treatment group: heat and electrical passages, GC and WA tests

PASSAGE	TREATMENT		WA	GC
Electrical	HC-EA/U		3	3
	HC-EA		3(2)*	3
	HA-EA/U		2	3(2)*
	HA-EA		2(3)*	3
	ST-EA:	Pre-EA	2	3
		Post-EA	3	3
Heat: Concrete				
	HC-EA/U		2(3)*	2
	HC-EA		2	2(3)*
Abstract				
	HA-EA/U		2	2(3)*
	HA-EA		2	3

*The numbers in parentheses represent close second choices. A good case could probably be made for selecting each of these as the appropriate number of dimensions for the solutions in question.

Judging from Table 6, though, students generally had three-dimensional representations of electrical concept interassociation, and generally two-dimensional configurations of heat concept interrelations. In addition, the graphic construction (GC) test more often resulted in three-dimensional representations, even including the heat passage structures, whereas the word-association (WA) test more often produced 2-dimensional configurations.

Comparison of Cognitive and Content Structures

Since visually comparing each of the twenty cognitive structure configurations to its appropriate content configuration can become a long and potentially tedious venture (especially when many of the representations might be more accurately depicted in three dimensions), it will be left to the interested reader to undertake at his/her leisure. Instead, what will be presented are any important highlights of those visual comparisons that appeared relevant to the outcome predictions of the study and the results of matrix correlations obtained between content and cognitive structures.

Electrical passage. Heeding Preece's (1976b) argument against the use of Euclidean distance computations as a means of determining the distance between two matrices, intermatrix correlations were calculated between WA and GC similarity matrices for each group and the electrical content digraph similarity matrix.[2] And these correlations are displayed in Table 7 .

Table 7

Correlations between treatment groups' cognitive structures of the electrical passage, as measured by the WA and GC tests, and the electrical content structure

[2]As a point of interest, preliminary calculations of Euclidean distances between several pairs of matrices did not reveal differences where they were visually apparent.

(Table 7 continued)

TREATMENT		TEST OF COGNITIVE STRUCTURE WA	GC
(1) HC-EA/U		.30	.21
(2) HC-EA		.35	.21
(3) HA-EA/U		.29	.25
(4) HA-EA		.33	.17
(5) ST-EA:	Pre-EA	.41	.39
	Post-EA	.37	.42

While the differences are not large among the correlations presented in Table 7, some definite trends are apparent. The most striking result is that the group receiving the structure-training first passage produced electrical cognitive structures, both before and after reading the electrical passage and on both the GC and WA tests, that more highly approximated the electrical content structure than any other group. While the WA test in this group resulted in a slightly higher correlation than the GC test prior to the group's reading the electrical passage, this trend reversed itself in the structures produced after the passage had been read. For the remaining groups, the WA test resulted in cognitive structures somewhat closely approximate to content structure than the GC test did.

Comparing groups 1 and 2 to groups 3 and 4--or, in other words, those groups receiving a facilitative first passage as opposed to those receiving a non-facilitative first passage--indicates that the electrical cognitive structures of those in the facilitative conditions were

slightly closer to the content structure on both tests than the cognitive structures of those in the nonfacilitative groups. The one exception to this occurs in the comparison between Group 1 and Group 3 on the GC test; here, the cognitive structure of those in the nonfacilitative (HA-EA/U) group was slightly closer to the content structure than that of the facilitative (HC-EA/U) group.

Looking at the differences between groups that underlined versus groups that did not reveals a mixed bag of results. Correlations between content and cognitive structure were slightly higher for non-underliners than for underliners on the WA test but not on the GC test. The cognitive structure of underliners in the HA-EA condition (Group 3) more closely approximated the content structure than did the corresponding non-underliners (Group 4); no difference appeared between underliners and non-underliners in the HC-EA conditions (Groups 1 and 2).

On the basis of eyeballing comparisons among the visual representations of electrical cognitive structures, and between them and the content structures, representations resulting from the GC test for each group and the corresponding configurations produced from the WA test appeared more similar to one another than either did to the content structure.

Heat passages. Intermatrix correlations were also computed between heat content and group cognitive structures

for those groups that read an initial heat passage, either abstract or concrete. Unfortunately, no useable coefficients resulted, primarily due, it is suspected, to the large number of zero entries in the heat concrete and abstract content matrices. Almost two-thirds (66%) of the cells in both 16 x 16 matrices contained zero entries. Again, however, eyeball comparisons suggested that the cognitive structures of the respective groups were more similar across test type than to either the heat concrete or heat abstract content structure.

CHAPTER IV

DISCUSSION

Accepting the fact that knowledge of the structure of a discipline is what teachers attempt to communicate in classrooms and what has an enormous impact on what and how well learning will occur does not guarantee possession of the appropriate tools by which to measure that structure, either within the subject matter or in the student's head. Measures of concept relatedness, under the assumption that the structure of meaning entails such relatedness, have been offered by Shavelson and others, in combination with hierarchical, scaling, and graphic analyses, as means of representing content and cognitive structure and evaluating their correspondence. While these techniques have been shown to depict some level of logical structure and interrelatedness, whether the structure they reveal is actually at the level most meaningful and useful to educators remains an open question. Attempting to determine an answer to this question, then, was one of the major purposes of this study. Specifically, it was expected that if the sort of structure uncovered by these types of indicators is learnable by rote with no real comprehension of the material required, the cognitive structure might appear to approximate the relevant content structure but recall dependent upon comprehension would be low. If, on the other hand, these techniques are

indicative of a deep level of structure, then recall should be high if the appropriate cognitive structure can be taught and approximates content structure. Furthermore, differences among students in different states of learning after equivalent instruction should become evident upon the application of these measures.

The second aim of this study concerned a nonspecific facilitative transfer effect found in the learning of complex materials by Royer and his associates and explained, to data, only in terms of initially presented information acting as a knowledge "bridge" between that which students already know and that which they are subsequently required to learn. It was hypothesized here that applying Shavelson's measures for representing cognitive and content structure to this situation might give us a handle on what nonspecific transfer actually is.

With respect to the first question raised by this study, results support the contention, first raised as a possibility by Rothkopf and Thurner (1970), that the sort of structure being measured here can be taught so that cognitive structure approximates content structure but with little resultant gain in comprehension or subsequent recall. Idea-unit recall of the group which received the structure-training initial passage was second lowest of all the treatment groups and no different from recall of the nonfacilitative groups combined. The cognitive structures of this

group, however, (as measured both before and after second passage reading) more closely approximated the electrical content structure than any other group. This calls into question, then, the usefulness of association measures for evaluating the cognitive structure that accrues from school learning, since it appears that a more superficial level of structure is being tapped than is absolutely desirable. Following in the vein of Rothkopf and Thurner (1970), it would appear that the students in the structure-training treatment group learned to relate the key concepts as they were related in the instructional material, but without a full understanding of the meanings of these relationships.

Bearing on this issue to some degree and yet offering possibly opposite conclusions are the effects of underlining on recall and structure found in this study. Underlining was originally selected as a task expected to draw students' attentions to the key concepts inherent in the instructional material without demanding full comprehension or processing of the information contained there (a scanning function, perhaps). A reasonable prediction based on this expectation, then, would be that students who underlined would more closely approximate, in their cognitive structures, the content structure of the passage they underlined than would students who did not underline. This is, of course, assuming that the tests measure appropriate structure. Their recall, however, would probably not be quite as high, given that

they did not process the information as fully. In the event that the measurement methods are invalid for measuring appropriate structure, no differences in either structure or recall as a function of underlining would be expected; if anything, groups who underlined might recall slightly more if underlining has more of a note-taking function than a scanning for key-concepts function. Results did not bear out either prediction, however. Instead, underlining interacted with the type of first passage (heat concrete or abstract) in its effects on recall and it produced rather difficult to interpret results in the structure measures. Given these results, the question that immediately arises concerns the purity of the treatments, whether, in fact, students actually followed their specific instructions to underline key concepts or not. Observation during the experimental sessions revealed that two types of confounding did occur, but both at a low frequency. A few students in the underlining conditions failed to underline and a few more underlined where they were instructed not to. There appeared to be, too, a high correspondence between those students who did not follow instructions and those who failed to return for the second experimental session; since the latter were replaced in the experiment, some of the possible confounding was avoided.

Confounding aside, then, and considering recall first, underlining tended to improve remembering of idea units in

the facilitative condition (concrete first passage), but it definitely interfered with recall in the nonfacilitative condition (abstract first passage). One possible interpretation of this is that underlining may take on more of a note-taking function in the case where the student already understands fairly well what (s)he is reading, whereas when the student does not understand the material well, underlining can only serve to highlight key concepts. It would be interesting to note what was actually underlined in each case; they could conceivably be quite different, underlinings in the former case relating fairly directly, perhaps, to the student's prior knowledge and in the latter, reflecting only the key concepts selected for the material.

The effect of underlining on structure, while not large, also does not indicate that underlining draws attention to key concepts in such a way as to improve the correspondence between content and cognitive structure. Only in one pair of groups, on one test, was the correlation between content and cognitive structure any larger for the underliners. It might be possible to suggest from this, too, that some degree of comprehension is related to these structure measures.

An issue to consider briefly here is the question of the appropriateness of using matrix correlation to determine closeness of correspondence between different structures. Preece (1976b) argued against Euclidean distance computations

because he could demonstrate differences in distance between structures without concurrent changes in measure of achievement. We have the opposite problem here, however. A preliminary application of the distance analysis to structure data did not discriminate among groups which, in fact, differed on the recall measure. Is that a problem with Euclidean distance analysis, or is that a problem of the original measure of structure? The answer simply is not clear.

A strike in favor of using matrix correlation over Euclidean distance as an index of correspondence, however, occurs when we consider the possibility that some structure might be a scaled replicate of another. If, for example, the similarity values in one matrix were exactly twice the corresponding values in a second matrix, a Euclidean distance analysis would indicate a large discrepancy between them while the multidimensional scaling routine would produce identical-looking structures. A matrix correlation, on the other hand, would not produce such spurious results; a perfect correlation would result with identical structures. One problem, though, with the correlation index as it was used here is that the values in the original similarity matrices were used as input, rather than the values of the solutions produced by the scaling routine. Because the scaling routine was used to find the best-fitting solutions for the original data, using the solution distance values in the correlation calculations would have been more appropriate.

In any event, the correlations found here are by no means large and must remain suggestive rather than conclusive.

Turning now to interpretations of the actual multidimensional representations of content and cognitive structure, and what they may have to offer us in the form of an explanation for the facilitative learning effect (once again replicated), we find both hope and despair. Despair first. Going by any of the guidelines of the relationship between stress and goodness of fit in finding both the presence of structure not due to chance and its appropriate dimensionality (Kruskal, 1964a; Klahr, 1969; Stenson & Knoll, 1969; Wagenaar & Padmos, 1971), then all of the representations recovered for the cognitive structures are poor. What is worse is that even the event "that the null hypothesis of randomness has been rejected is probably not sufficient to ensure that there is any useful structure in the data" (Spence, 1974, p. 267). Error in the cognitive structure data would certainly explain some of the lack of fit, but beyond that, multidimensional solutions via the Kruskal-Shepard technique do not look especially promising for the representation of this sort of data. A more promising technique for this situation might be the Tucker-Messick points-of-view analysis (Tucker & Messick, 1968). Also a multidimensional scaling routine, this analysis operates on the proximity matrices of individual subjects and groups

greater the number of key concepts or the number of responses per concept on the WA test, the greater the time involvement for scoring. And as for the expense involved in analyzing the results of the proximity data, although computer algorithms exist for multidimensional scaling routines, they are long-running (about 20 seconds for one solution) and require considerably more memory space (~175,000 bits) than the average program, all of which makes them costly to run on a routine basis. Perhaps, with an increase in technology, the cost and time limitations will be reduced and make the procedure more feasible to use than it currently is.

On a purely research level, however, the techniques remain intriguing and the potential for their use in applied settings still exists. The data-collecting procedures (such as the WA or GC tests) do assess some sort and degree of interrelatedness and may, indeed, be useful for collecting certain types of information. But certain methodological gaps need to be filled in order to realize this potential and make these techniques more widely applicable in an evaluative capacity, and a look at these shortcomings would certainly be productive.

Tackling the interpretability problem with respect to the multidimensional scaling solutions would seem to be the first order of business, and this encompasses the issues of finding criterial solutions against which to judge student cognitive structure, finding ways of determining the best

them according to their similarity. Students who have structured concepts similarly, then, would be grouped and their data analyzed to produce a representative configuration for their "point of view." Because of likely individual differences in background and amount learned among subjects in each of the treatment groups in this study, applying the Tucker-Messick routine might well produce more interpretable conglomerate structures than were produced by the Shepard-Kruskal technique. In addition, subgroups of students might be identified and their cognitive structures studied in relation to the content structures.

According to Shepard (1972), Kruskal (1964a), and Subkoviak (1975), ultimate choice of dimensionality and configuration is left up to the discretion of the experimenter; almost anything goes if it aids the researcher in the interpretation of his or her results. But that brings us to another, ever recurring, problem: interpretability. The representations recovered in this study from cognitive and content structure summary matrices offer little more insight into ways of improving interpretability than any of their predecessors. When a particular structure is not known or expected _a priori_, then trying to recover one that is both meaningful and useful is not an easy task. Axis rotation appears also to be at the discretion of the researcher, and it is often unclear as to precisely what orientation the axes should take. And if we are limited to merely extracting

clusters of similar concepts because of interpretation difficulties then we are probably not taking the fullest advantage of what the analysis can offer in terms of dimensionality. The problem of how similar is similar also arises once again. Without more standard procedures for determining how closely corresponding two representations are, comparisons of student cognitive structure to teacher cognitive structures, or student structures to content structures, for diagnostic purposes, will never be feasible.

After so much bad news, what's the good news? What looks promising is the possibility of shedding more light, through these analyses, on the sources of facilitative transfer occurring in the HC-EA treatment groups. There were seven concepts appearing in all of the passages, with one additional concept appearing under one label in the heat passages and under another in the electrical passage. And comparing the content structures of the three separate passages (heat concrete, heat abstract, and electrical), we can see that several similarities exist between the heat concrete and the electrical passages, whereas few are evident between the heat abstract and either of the other two passages. If the heat concrete configuration is rotated 90^{o}, then the concepts METAL, CONDUCTOR/CONDUCTIVITY, and ELECTRON line up along the same dimension in both the heat concrete and electrical passages, and the concepts STRUCTURAL REGULARITY and BONDED MOLECULE align along the same dimension.

It seems possible, then, that the interconcept relationships existing between the concepts in those two groups of concepts are acquired during the reading of the concrete heat flow passage and then are available to facilitate learning of the other relationships in the electrical passage. Since Royer and Cable (1976) demonstrated the facilitative effect using entirely abstract passages, which had either inserted illustrations or analogies, however, there is still some question as to why the heat concrete, but not the heat abstract, content structure resembles that of the electrical content in their common concepts. Still, although Geeslin and Shavelson (1975) recommend that "studies should examine instructional variables which lead to a closer correspondence between content structure and cognitive structure" (p. 37), perhaps studies using these sorts of analyses should also examine the correspondence between the respective content structures altered by some instructional variable in order to determine why some facilitative effect occurred.

Summary and Suggestions for Future Research

Results of this study indicated that proximity measures, with their correspondent scaling analyses, should be approached with some caution if the purpose for using them is to evaluate learning by comparing structures to content structures. It appears that the structure measured by these assessment techniques can be trained to some degree without

teaching for comprehension and without promoting an increase in recall and those would certainly not be among the goals of any educator. A related problem arising when we talk about measuring "cognitive" structure is the fact that all of the concepts used in these techniques must be prespecified. That, in itself, automatically limits the structure that can emerge. There is no room for student idiosyncracy, except within the limits of those predefined concepts, and no possible assessment of student prior knowledge of that material involving various and sundry related facts. While these may all affect how the configuration of interest is learned--how much information gets processed, what material is processed, and what a final configuration might look like--none of these effects can be reasonably assessed using already specified concepts.

Another cautionary note with respect to the use of these types of measure and analyses in an educational evaluative setting concerns simply the time and cost involved in using them. While these factors have not yet been mentioned by any other researcher, they certainly cannot be denied when considering the pragmatic utility of applying proximity measures and multidimensional scaling analysis on a large scale. While developing and administering the word-association or graphic construction tests (or virtually any other proximity measure) may not be tedious or time-consuming, scoring student responses most definitely is both, and the

solution for the structures produced by students, and finding quantitative measures of comparison between the student structures and the criterial structures. With respect to criterial solutions, we need to know whether experts in a subject area differ from one another in the manner in which they structure the subject matter concepts and whether they differ in methodical ways from the structure of the content itself. Only with that information can we decide what should comprise a criterial solution, or solutions, against which to evaluate student solutions. Finding "best" solutions involves the decisions regarding dimensionality and axes rotation, and advances in the methodology are needed here to develop standard, statistical bases upon which to make those decisions. And the need to find quantitative measures of comparisons for derived structures more or less speaks for itself; we need a standard procedure both for making judgments of similarity or difference between structures and for interpreting those judgments.

Other methodological issues that bear further exploration are those related to assessing prior knowledge of subject matter, which might also involve questioning the way in which the concepts to be rated are chosen, and those taking into account other student characteristics. The points-of-view analysis, or other analyses geared to revealing individual differences, might be one promising approach to the problem of assessing prior knowledge of a subject matter.

Subgroups of students having different backgrounds in a subject area could be identified and the differences in the way in which they structure the key concepts quantified. And that information could form a strong base from which to make predictions of changes in cognitive structure over learning and from which evaluate and interpret actual changes that do occur. Since the degree of prior knowledge about a subject possessed by a student might well influence what (s)he would take to be important concepts in future learning, other empirical ways of determining what concepts should be selected for the rating tasks ought to be explored. And other types of rating tasks, such as the card-sort, that will yield proximity data suitable for analysis in multidimensional routines warrant further research as to their sensitivity in tapping comprehension levels of cognitive structure. Finally, relating other student characteristics to their structuring of instructional concepts is certainly an area for further investigation.

There is no question but what this methodology and its application to the assessment of cognitive structure is in the early stages of development. And there is really no question as to the promise of the techniques and the importance of the assessment of cognitive structure. Once the methodological issues raised here have been dealt with and the technology advanced sufficiently, practical assessment of higher-order learning--what students have learned of the

content in question with respect to other students, with respect to their teachers, and with respect to the content itself--may become a reality.

REFERENCE NOTES

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APPENDIX A: Materials

General Instructions
Passage Reading Instructions
Word Association Test Instructions
Graph Construction Test Instructions
EA Passage
HC Passage
HA Passage
ST Passage

GENERAL INSTRUCTIONS

+ This study investigates several techniques for measuring and depicting the structure in people's memories that results when they study textual materials. The experiment will be conducted in two sessions. In the first session, you will read a short passage and then do two tasks involving manipulation of the key concepts in the passage. The second session will be virtually identical to the first except that you will be reading a different passage and doing one additional memory task. Since some students will have additional instructions during the reading phase of the experiment, do not be surprised when others around you are not doing exactly what you are or are not reading exactly the same thing. _Just follow your own instructions_.

Are there any questions?

When you are told to do so, turn the page and read the specific instructions to yourself.

FIRST PASSAGE INSTRUCTIONS

Underlining

When told to begin, turn the page and read the passage slowly and carefully once. Then read it again and, as you read, underline what you think are the most important KEY CONCEPTS contained in the passage. These may be one word each or a short phrase but should reflect what you think are the most important concepts in the passage. When you are finished, turn the passage over and wait quietly until everyone is finished.

No Underlining

When told to begin, turn the page and read the passage slowly and carefully twice. When you are finished, turn the passage over and wait quietly until everyone is finished.

SECOND PASSAGE INSTRUCTIONS

Underlining

You will be given two minutes to read each page of the three pages in this passage. As you read, underline key concepts as you did in the first passage you read. Remember that key concepts may be one word each or a short phrase but should be what you think are the most important concepts in the passage. The experimenter will tell you when to go on to the next page. Once you have turned a page, do not refer back to it or previous pages.

Do not begin until you are told to do so.

No Underlining

You will be given two minutes to read each of the three pages in this passage. If you finish reading a page before the two minutes are up, start reading it again. The experimenter will tell you when to go on to the next page. Once you have turned a page, do not refer back to it or previous pages.

Do not begin until you are told to do so.

WORD ASSOCIATION TASK

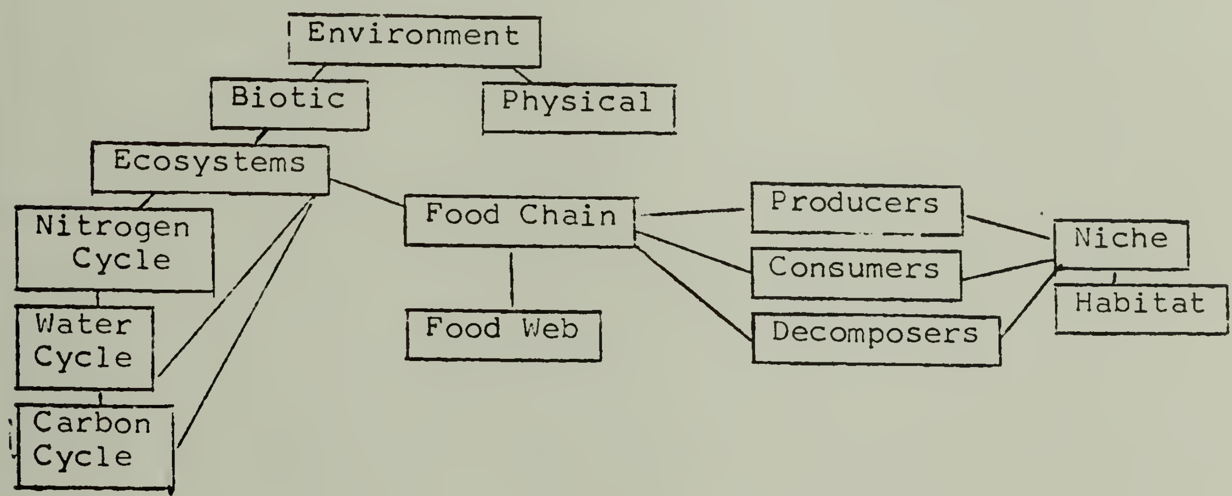
Printed at the top of each page in this booklet is a word or short phrase that appeared in the passage you just read. On the lines provided below the word, write down as many words (or concepts) as you can think of that are related to the printed word. You will have only one (1) minute per page so think fast and write down as many related words as you can.

Do not begin or turn to a new page until you are instructed to do so. The experimenter will tell you when to turn each page.

GRAPH CONSTRUCTION INSTRUCTIONS*

This is a test that asks you to arrange concepts on a sheet of paper. You should arrange the concepts in the way that is most meaningful to you. Concepts which you think are closely related will be placed close together on the paper. The concepts may be clustered into tight groups or spread out. You should connect concepts which are related by lines.

For example, the following is a sample arrangement for ecology.



Not all the important concepts are included in this example, and you may disagree with the way they are related. However, it does illustrate the kind of arrangement you should make. Note, for instance, that producer is much more closely related to consumer and niche than it is to carbon cycle.

Attached to this sheet of instructions you will find a sheet of paper and an envelope containing _____ labels. Each label has a concept from the passage you just read written on it. Arrange the labels on the paper. When you are satisfied that you have represented the concepts in the most meaningful way based on what you remember from the passage, peel off the back of the label and affix it in position.

Are there any questions about what you are supposed to do?

*Adapted from Rudnitsky and Garlock (1977).

Electrical conductivity is a property present to various degrees in materials and concerns the extent to which that material allows the flow of electrical current through itself. The current flow actually consists of many negatively charged electrons migrating toward an attracting positive pole. This attraction is similar to the attracting characteristics of opposite magnetic poles.

LThe capability of a material to conduct electricity is determined by a number of physical properties: the atomic and crystalline structure of the material, the thermal state of the material; and magnetic influences on the substance.

In general, the most efficient conductors of electricity are metallic in nature. Metals are highly efficient conductors because they possess two physical properties critical to efficient conduction. These features are the presence of unbonded electrons and a highly regular molecular structure. Sufficient magnification of a particle of metal would reveal an interior structure consisting of bounded molecules arranged in a systematic order. These regular structures are known as crystal lattices. A further examination of these structures would reveal considerable "open space" in and around the structures and that unbonded electrons were moving at random through these spaces.

When the negative and positive poles of a current source such as a battery are attached to a bar of metal free electrons from the battery pass into the bar. At the same time unbonded electrons from the metal are attracted by and begin to flow into the positive pole of the battery. The abundance of electrons in one area of the bar coupled with the reduction in electrons in the other end results in a stabilization action whereby electrons are migrating from the negative to the positive pole of the battery.

Because the free electrons play an integral part in the flow of current through a medium, it is important to note that the presence of relatively few of these loosely bonded particles would greatly restrict the potential current flow. Likewise, the degree of regularity within the crystalline structure influences the conductive efficiency of the medium. The relationship between the internal structural regularity and the passage of electrons through the medium is such that a symmetrical structural array permits a greater number of electrons to pass, and, conversely, an irregular structure, by increasing the probability of collisions between the electrons and the molecular units would greatly decrease conductivity.

Two other factors which influence the degree of conductivity of a material are its thermal state and the presence of a nearby magnetic force field.

The degree of conductivity of a substance is dependent upon the thermal state of the medium because an increase in thermal energy results in a higher thermal agitation velocity among the crystalline structure units. The resultant increase in agitation velocity in turn increases the probability of collisions between the current electrons and the vibrating structural units. This increase in collision rate results in restricted current flow.

A magnetic force field can also decrease current flow. This decrease occurs due to a restriction in the conducting surface of the medium and the resultant increase in inter-electron collisions. The presence of a negative force field near a conductive medium would force the similarly charged electrons passing through the medium towards the side of the medium opposite the direction of the force field. The resultant crowding of the current electrons through such a restricted space will necessarily decrease the amount of current which can pass through the medium in a given amount of time. The presence of the force field not only restricts the conducting space of the medium but also increases the frequency of inter-electron collisions. As the moving electrons are initially repelled by the force field, in seeking to flow both towards the positive pole of the medium and away from the force field they will more frequently collide among themselves, thus further restricting current flow.

The term "heat flow" is a descriptive concept invented by man rather than a representation of physical reality. That is, we can not see, feel, hear, taste, or smell heat. Rather, what we can see and feel is a change in temperature. The idea of heat flow was invented to fill a gap in our logic. In this passage we will be discussing how heat is transferred from one location to another in a bar of metal such as iron. The term used to describe such transfer is known as conduction.

Heat transfer actually involves the transfer of molecular motion. In the case of conduction this transfer of motion occurs through a solid substance such as our bar of iron. If we were able to examine a bar of iron through an extremely powerful microscope, we would see that the interior consists of a series of regularly shaped and spaced structural units known as crystal lattices. In order to picture these lattices, imagine a box made of many tinker-toys, the inside as well as the outside consisting of joined parts. The solid round parts of the tinker-toys would correspond to the molecules within the crystal lattice. The interior of the bar consists of many of these "boxes" joined together. In our bar of iron, which is a good conductor of heat, each of the bonded molecules within the lattice has associated with it several "free-floating" electrons. Each crystal lattice, then, is an orderly array of molecules surrounded by a cloud of electrons which are not attached to any particular molecule, but are free to move at random through the lattice. You can picture this by imagining many tiny particles floating through the series of tinker-toy boxes.

In our bar of iron, the lattices making up the bar, and the electrons within the lattices,are all in constant motion. For the lattices, this motion consists of back and forth vibrations. The electrons are also in motion but moving at random through the lattices. When the entire bar of iron is at a constant temperature, the movement (agitation) of all the lattices and electrons is occurring at the same speed or velocity. Thus, if we were to look at the velocity of any individual lattice or electron, it would be about the same as the average velocity of all the rest of the lattices and electrons in the bar. The agitation velocity corresponds to the temperature in the bar. That is, as the temperature of the bar increases, there is also an increase in agitation velocity.

If we now heat one end of our iron bar, several things happen. The free electrons and the lattices near the heat source begin to move more rapidly than those in the remainder of the bar. This increased agitation results in a higher number of collisions between the free electrons and the bonded atoms and among the free electrons themselves. These collisions agitate the atoms and electrons being struck and cause them to collide in turn with other nearby particles. The agitation occurring within one lattice produces a similar agitation within surrounding lattices. Eventually this increased agitation is transmitted the length of the bar. The transmission of agitation velocity corresponds to temperature changes throughout the bar. Thus, by applying a heat source to one end of the bar, we eventually produce a higher degree of agitation for all the lattices making up the bar, which is noticeable as an increase in temperature.

Two factors which affect the flow of heat in a bar of metal are pressure and impurities in the metal.

If pressure, such as a strain to twist the bar is applied, the flow of heat is slowed down. Using our tinker-toy model, we can see that each atom is connected in a regular and orderly fashion to surrounding atoms. If we twist one end of the bar while holding the other end steady, we may not only break some of the connections between the atoms but we will also destroy the regularity. Much of the energy an atom transfers in the heat flow collisions is lost because the distortion has moved the next atom slightly off target.

Imagine, for example, two situations with dominos (crystal lattices), the first being where dominos are lined up in orderly rows. If we topple the dominos in the front rank of each row, the toppling motion is quickly transmitted to the remaining standing dominos. However, if the standing dominos are arranged in a haphazard fashion, the toppling motion is only transmitted to some of the dominos; many will remain standing. Heat flow through a metal under pressure or not under pressure occurs in a similar manner.

The effect of an impurity in a metal also serves to reduce the efficiency of heat transmission. If we were to place some sizeable object (such as a pack of cigarettes) in our orderly array of dominos, we would see that the toppling motion would be reduced around the object. Likewise, the presence of some impurity in a bar of metal serves to reduce the transfer of agitation velocity in the orderly crystal lattice arrays. This is because the impurity breaks up the regularity of the crystalline structures, and absorbs some of the energy that might otherwise be transmitted through the metal.

The term "heat flow" is an abstraction invented by man rather than a representation of physical reality. That is, heat is not detectable by any of our sensory mechanisms. Rather, what we do detect is a change in temperature and the notion of heat flow was invented to fill a gap in our logic. In this passage we will be discussing how heat is transferred from one location to another within the confines of a metallic medium. The term used to describe such transfer is known as conduction.

Heat transfer is best conceptualized as the transfer of motion. In the case of conduction this transfer occurs through some solid physical medium, such as metal. If we were able to examine a bar of metal through an extremely powerful microscope we would see that the interior of the bar consists of a series of crystal lattices, with each lattice consisting of many tightly bonded atoms. In a metal which is an efficient conductor of heat, each of the atoms has associated with it one or more "free floating" electrons. Each crystal lattice, then, consists of an orderly array of atoms surrounded by a cloud of electrons which are not attached to any particular atom but are free to move at random through the confines of the lattice.

The overall regularity in the crystalline structure of a metal is highly significant in that substance's particular ability to more efficiently and more quickly transmit heat.

In a substance where the crystalline structure is irregular or randomized, much of the energy of the thermal agitation is lost in the vibrating of particles which have no significant contact with particles in the direction opposite the heat source. Under conditions of constant temperature throughout tne bar of metal, the individual crystal lattices making up the bar, and the free electrons within the lattices, have a velocity of thermal agitation that is roughly equivalent to the statistical average of the thermal agitation velocity for the entire bar. This velocity in turn corresponds to the temperature of the bar. As the temperature of the entire bar increases, there will be a concomitant increase in the velocity of thermal agitation. Within the crystal lattices the free electrons move at random but are deflected and scattered by collisions with other electrons or with the bonded atoms in the lattice.

If we now apply a heat source to one end of a constant temperature bar a number of things occur. The free electrons within the lattices near the heat source acquire a velocity greater than the electrons within the remainder of the bar. This increased agitation results in a higher number of collisions occuring between the free electrons and the bonded atoms and among the free electrons themselves. These collisions in turn agitate the atoms and electrons being struck and cause them to collide with other particles within the lattice. The agitation occurring within one lattice produces a similar agitation within surrounding lattices and eventually this increased thermal agitation velocity is transmitted the length of the bar.

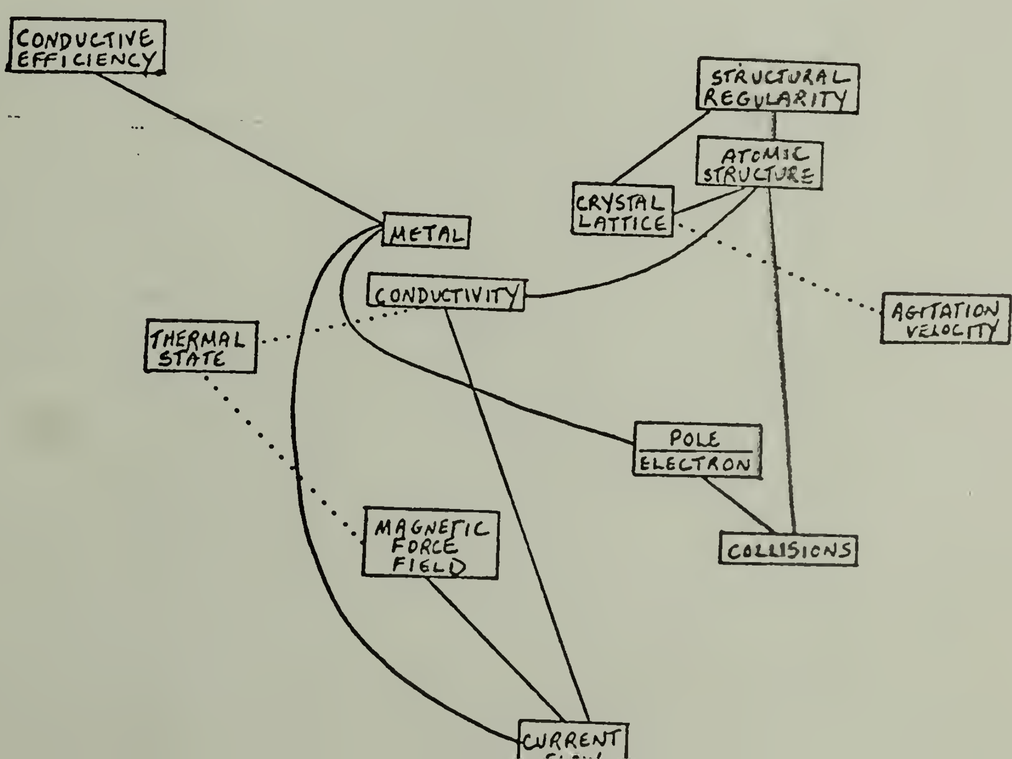
This transmission of agitation velocity is accompanied by temperature changes throughout the bar. Thus, by applying a heat source to one end of the bar we eventually produce a higher degree of thermal agitation for all of the lattices making up the bar. This increased agitation in turn increase the temperature of the entire bar.

Two factors which affect the flow of heat in a bar of metal are pressure and impurities in the metal. The application of pressure to a heat conducting medium produces a distortion of the crystalline structure with a resulting loss in the efficiency of the material as a heat conducting medium. The reason for this is twofold. First, pressure serves to break the bonds between the crystal arrays. Second, the pressure distorts the symmetry of the crystalline structures. Both of these factors result in a disturbance of the thermal agitation. Units which were previously directly colliding with each other will now only obliquely collide, with a resultant loss or waste of energy. Collisions of the latter form are prohibitive to heat flow.

The presence of a foreign particle or impurity in the chemical composition of the metal also reduces the efficiency of heat transfer in the medium. This is because the particle produces a distortion in the structural symmetry of the crystal lattices. The result is that some of the molecules in the medium will be moved into oblique positions, with a resultant loss of efficiency of thermal agitation transfer. The impurity produces this loss of efficiency in two ways. It absorb s some of the energy instead of passing it on, and because of the fact that the impurity is not as structurally bonded as the crystal lattices, it moves erratically thereby disturbing the normal transfer of energy.

In any kind of instruction, the important concepts are related to one another in some way, and it is the teacher's job to convey those interrelationships to students, One way of portraying relationships among concepts is to picture them as in the following diagram, which shows how thirteen important concepts having to do with electrical conductivity are interrelated. These thirteen concepts are conductivity, current flow, pole, metal, electron, structural regularity, crystal lattice, atomic structure, collisions, conductive efficiency, thermal state, magnetic force field, and agitation velocity. Take a moment to study the diagram.

The way to interpret the picture and determine what sorts of relationships exist among the concepts is to understand and follow two basic rules. First, concepts that occur close together spatially are highly associated within the phenomenon of electrical conductivity. Therefore, thinking of one should give rise to thinking of the other, and both should elicit the same, or nearly the same, set of additional related concepts.

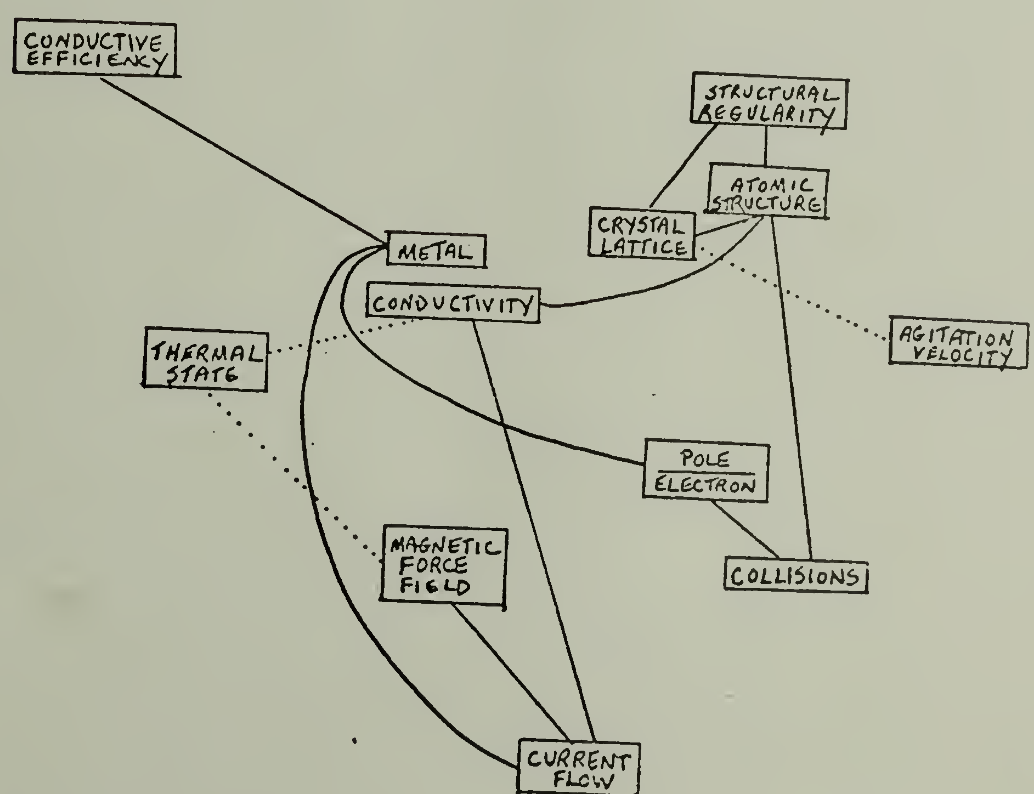


Second, the lines connecting certain concepts portray the directness of relationship between those concepts. Solid lines mean that the direct connections between concepts are strong whereas dotted lines indicate that the direct links are fairly weak. While concepts may be directly related, they might still evoke somewhat different sets of associated concepts. An example of the difference between closeness of association (Rule 1) and directness of relationship (Rule 2) might be found in the interrelationship between cat, dog, and mammal. Cat and dog are directly related to mammal in that they are examples of it. But when one thinks of cat or dog, mammal does not immediately come to mind, and vice-versa. Cat and dog, however, are high associates of each other, since thinking of one quite readily brings to mind the other. Both also tend to elicit similar thoughts, but they are not directly related in the way each is related to mammal.

Looking back at the diagram and following rules 1 and 2, you can see that in electrical conductivity, certain groups of concepts bear high, but not necessarily direct, association to one another. Metal and conductivity, for example, are highly associated but not directly related. Crystal lattice, structural regularity, and atomic structure are closely associated and related to one another directly and strongly. Pole and electron occupy nearly the same point on the diagram, which makes them very closely associated, and they are also directly connected, a fact which is not too clearly shown in the diagram. Finally, collisions is quite highly associated with pole/electron and directly related to them as well.

Considering the remaining direct relations among concepts, you can see that metal is directly and strongly related to conductive efficiency, current flow, and pole/electron. Conductivity is strongly connected to current flow and more weakly related to thermal state, which is itself also weakly connected to magnetic force field. Magnetic force field is strongly related only to current flow. While also being directly related to structural regularity and crystal lattice (which are themselves connected), atomic structure is strongly connected to both conductivity and collisions. Finally, agitation velocity is weakly connected only to crystal lattice.

Keeping in mind what it means for concepts to be directly related versus highly associated, study the diagram of the structure of electrical conductivity concepts once again, reprinted below.



APPENDIX B: Stress Functions, Scaling Solutions

Figures B-1, B-2, B-3: Stress as a function of dimension for the content structure solutions of the E, HC, and HA passages, respectively

Figures B-4 through B-23: Stress as a function of dimension for E and H cogntiive structures, all groups and tests

Figures B-24 through B-26: Multidimensional scaling solutions for the E, HC, and HA passages, respectively

Figures B-27 through B-46: Multidimensional scaling solutions for the E and H cognitive structures, all groups and tests

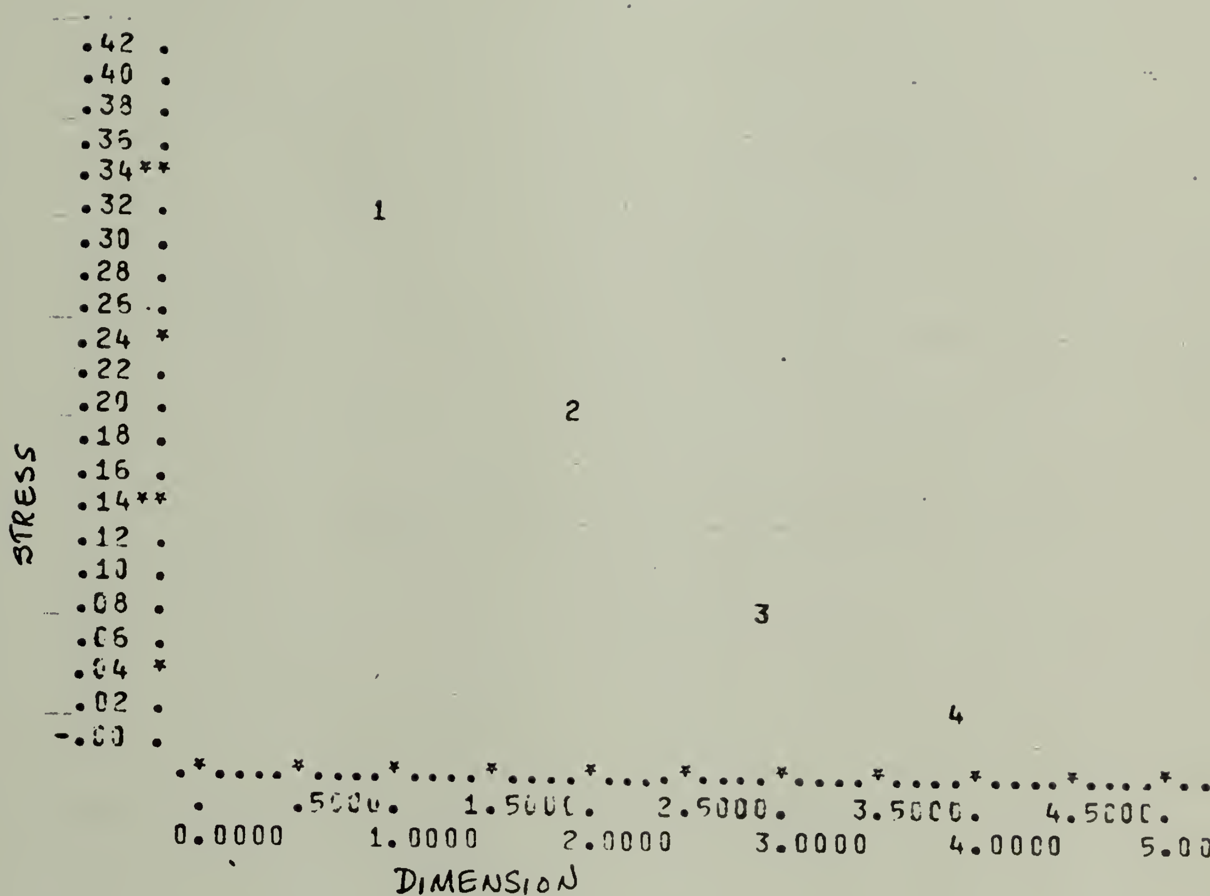


Figure B-1: Stress as a function of dimension for the electical content structure.

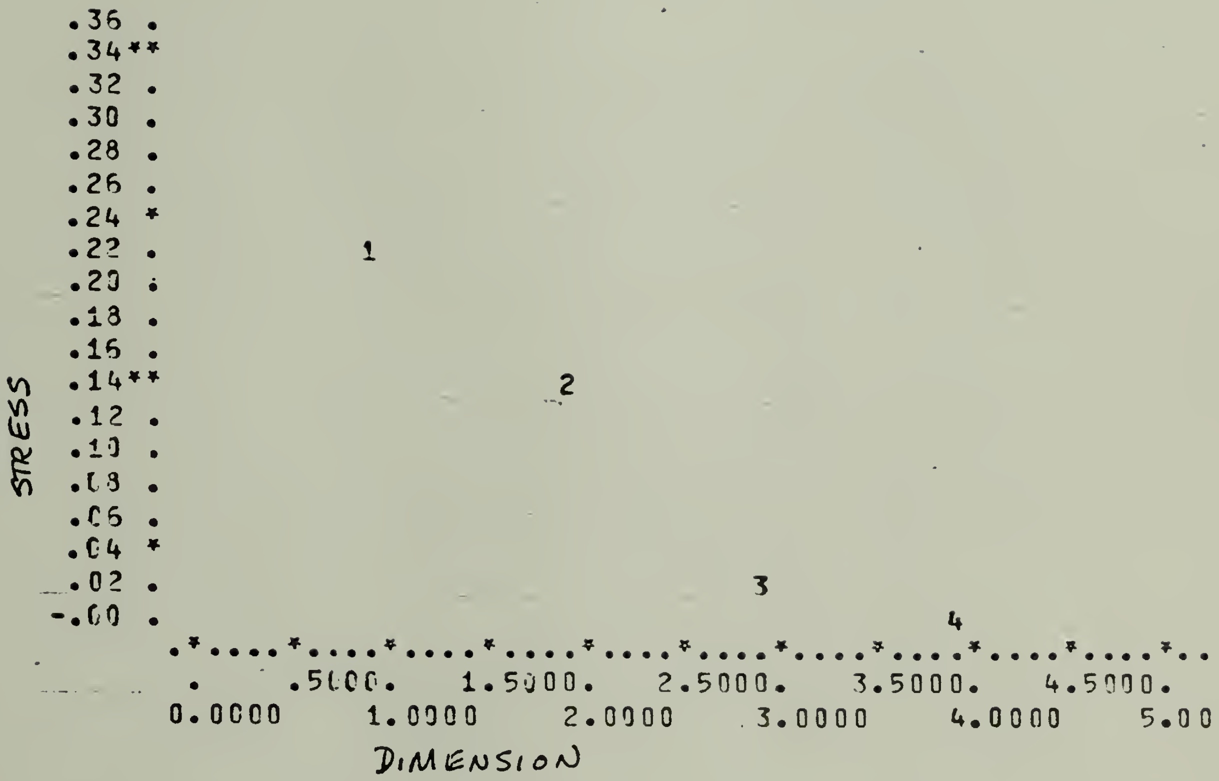


Figure B-2: Stress as a function of dimension for the heat concrete content structure.

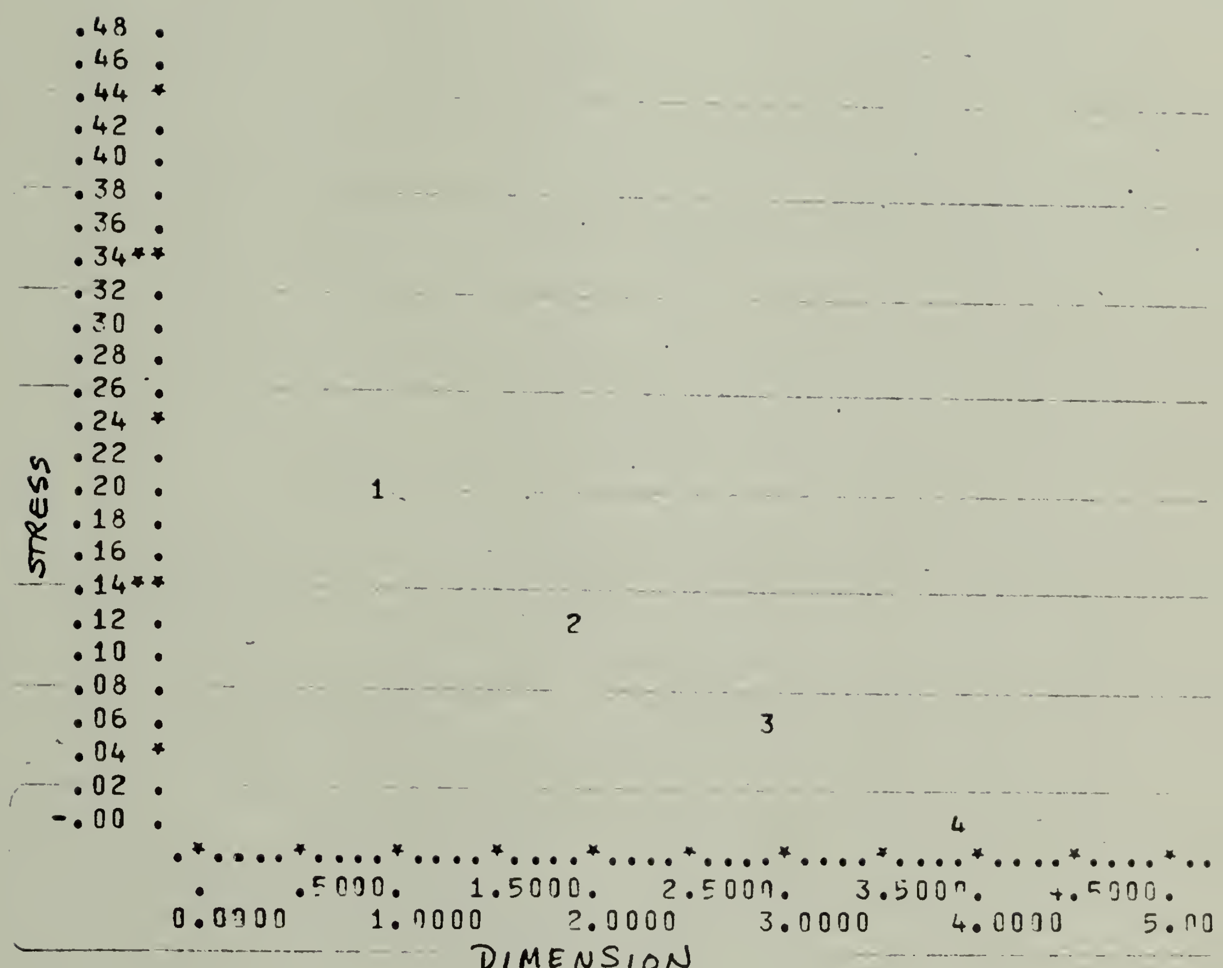


Figure B-3: Stress as a function of dimension for the heat abstract content structure.

PLOT OF STRESS VERSUS DIMENSION EA DISTANCE, HC/EA(U)

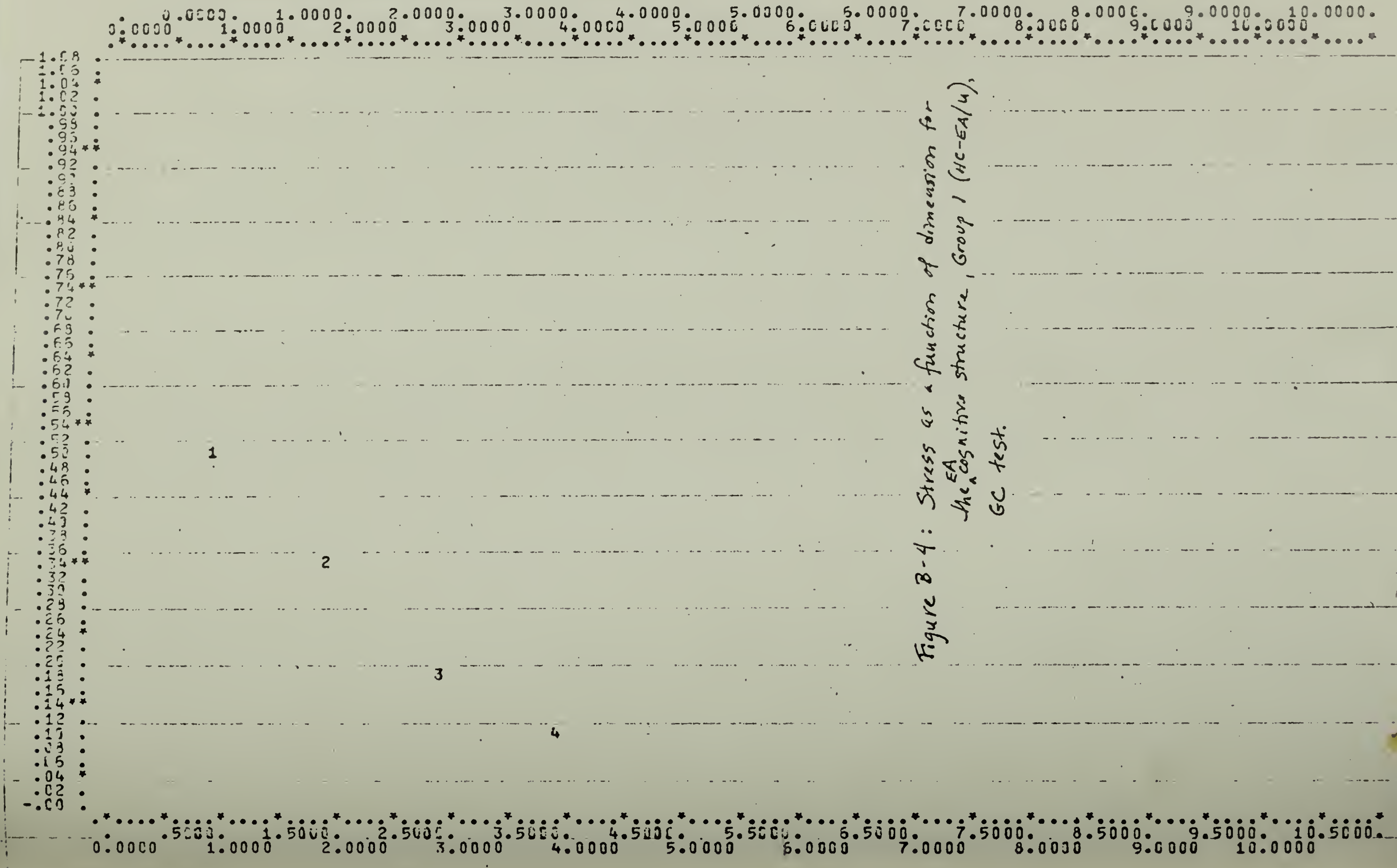


Figure B-4: Stress as a function of dimension for the EA cognitive structure, Group 1 (HC-EA/u), GC test.

PLOT OF STRESS VERSUS DIMENSION EA RELATEDNESS, HC/EA(U)

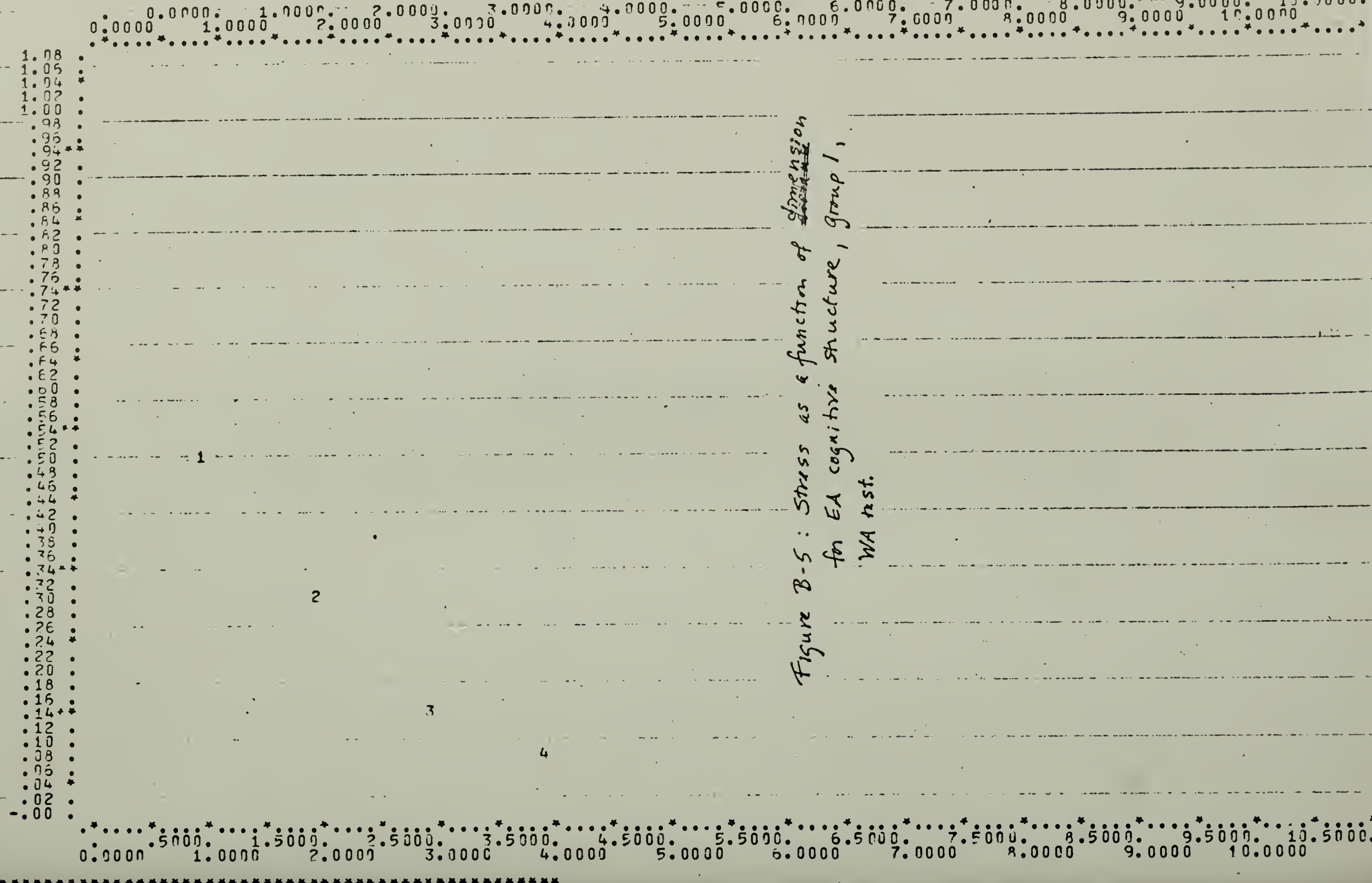


Figure B-5: Stress as a function of dimension for EA cognitive structure, group 1, WA test.

PLOT OF STRESS VERSUS DIMENSION EA DISTANCE, HC/EA

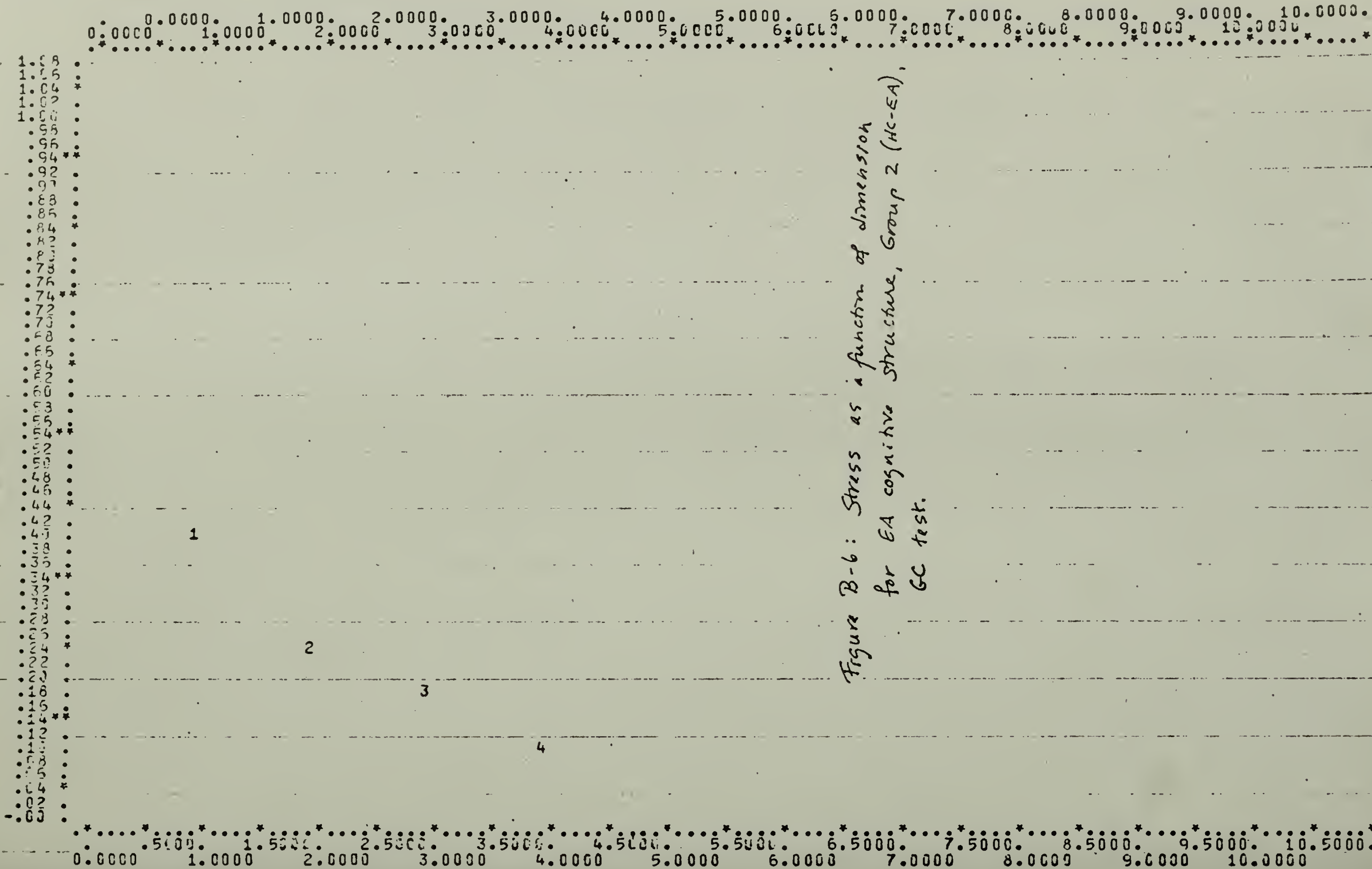


Figure B-6: Stress as a function of dimension for EA cognitive structure, Group 2 (HC-EA), GC test.

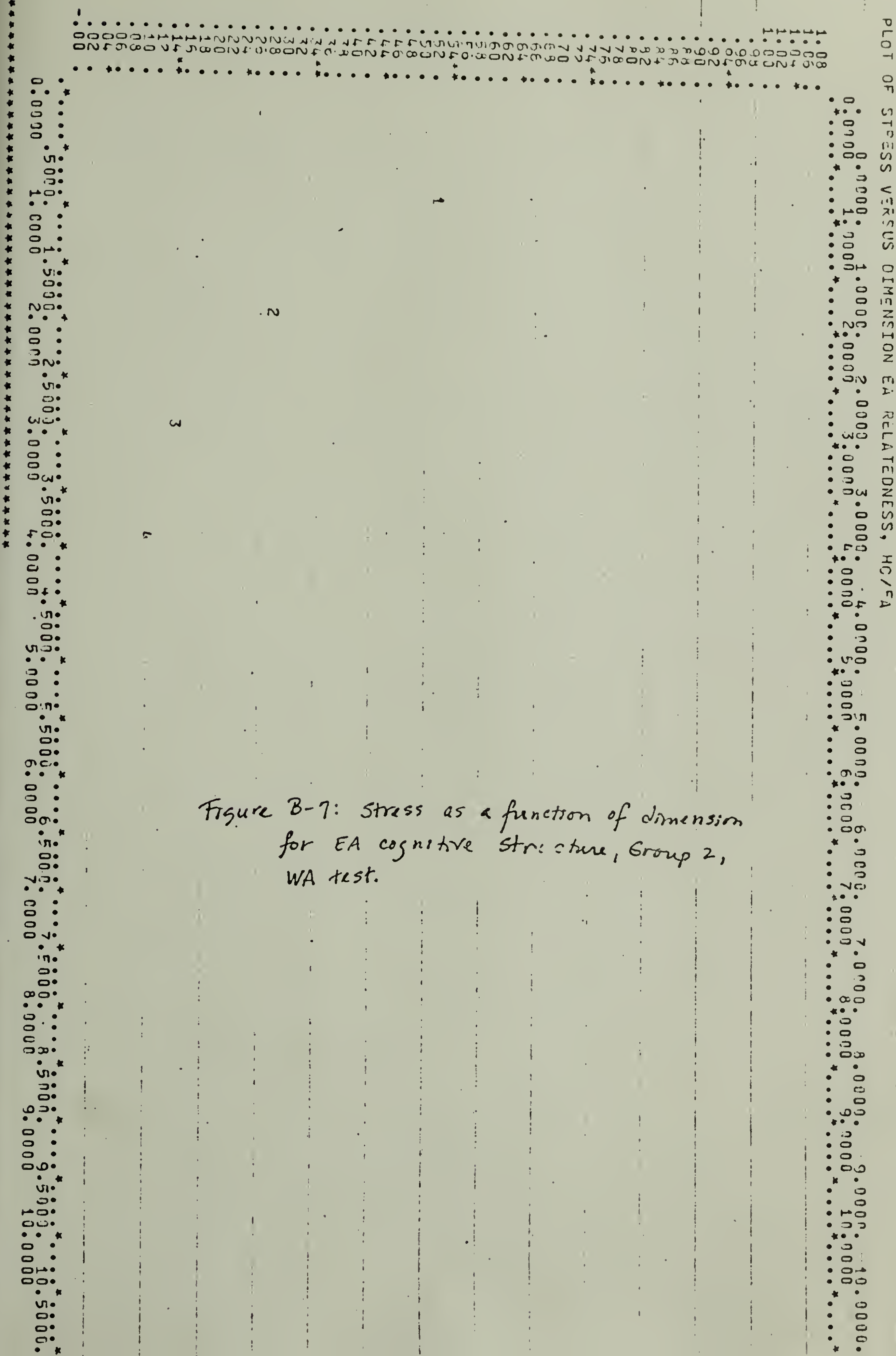


Figure B-7: Stress as a function of dimension for EA cognitive structure, Group 2, WA test.

PLOT OF STRESS VERSUS DIMENSION EA DISTANCE, HA/EA(U)

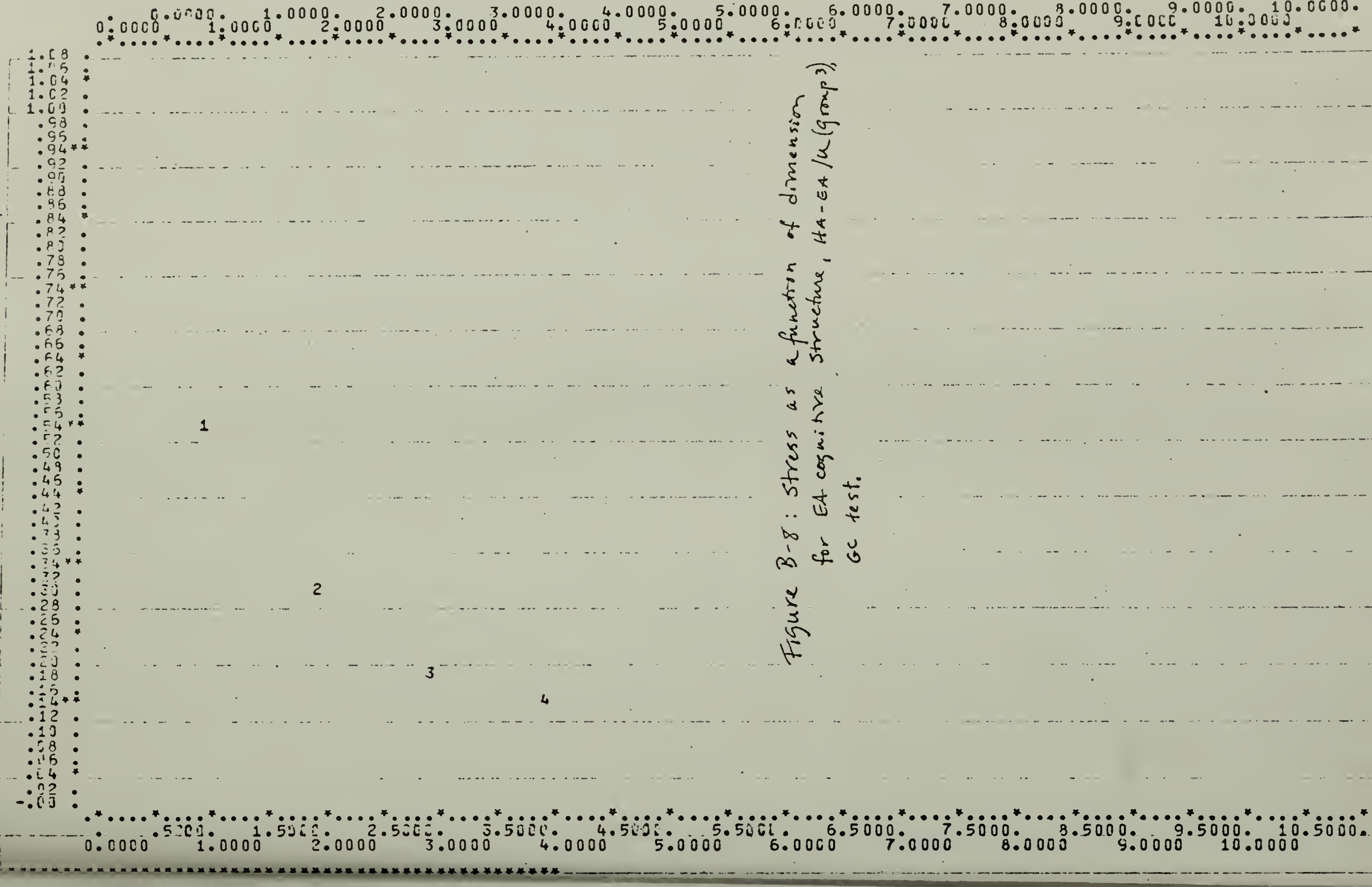


Figure B-8: Stress as a function of dimension for EA cognitive structure, HA-EA/U (group 3), GC test.

PLOT OF STRESS VERSUS DIMENSION EA RELATEDNESS, HA/EA(U)

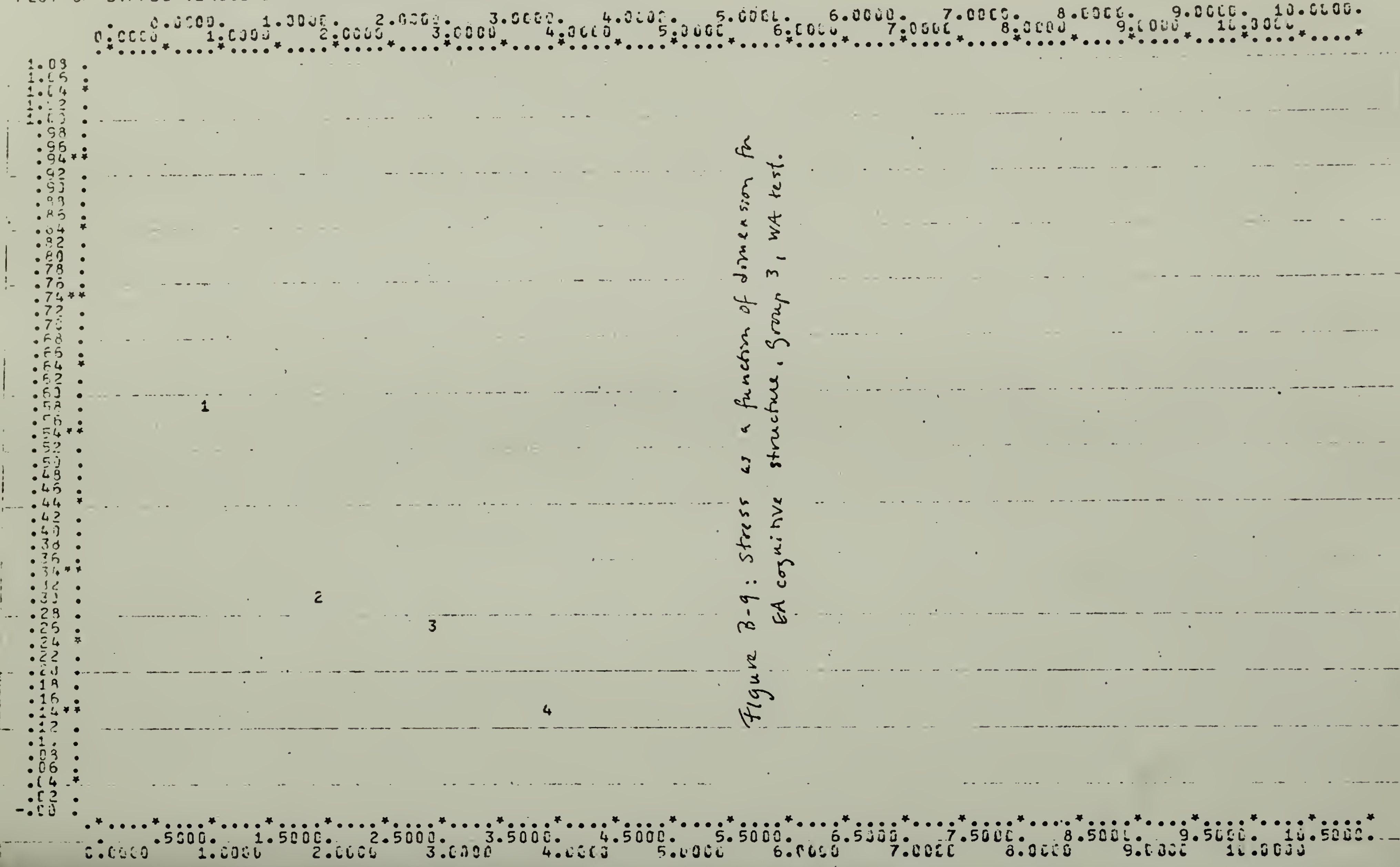


Figure B-9: Stress as a function of dimension for EA cognitive structure, Group 3, WA test.

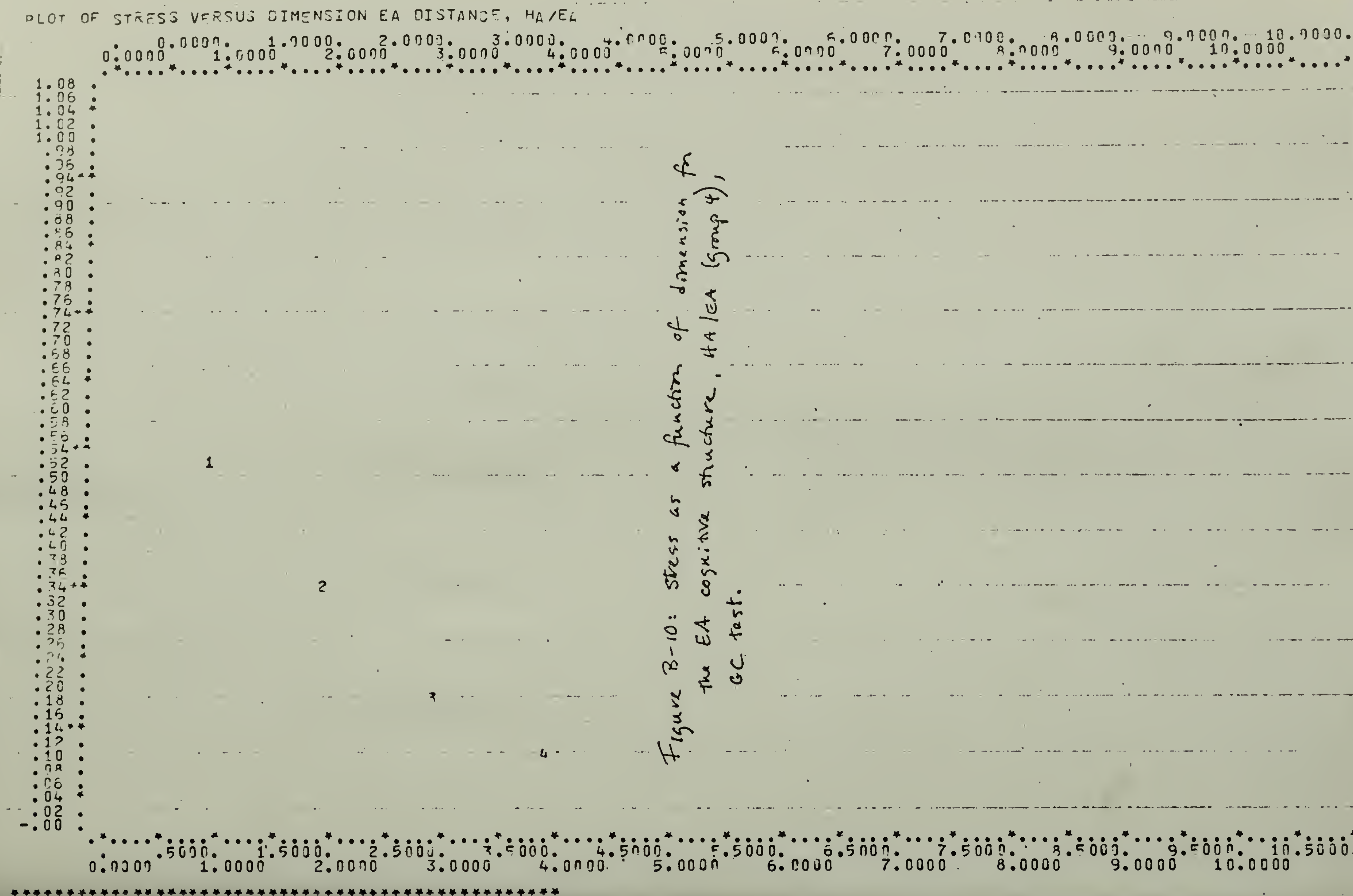


Figure B-10: Stress as a function of dimension for the EA cognitive structure, HA/EA (Group 4), GC test.

PLOT OF STRESS VERSUS DIMENSION EA RELATEDNESS, HA/EA

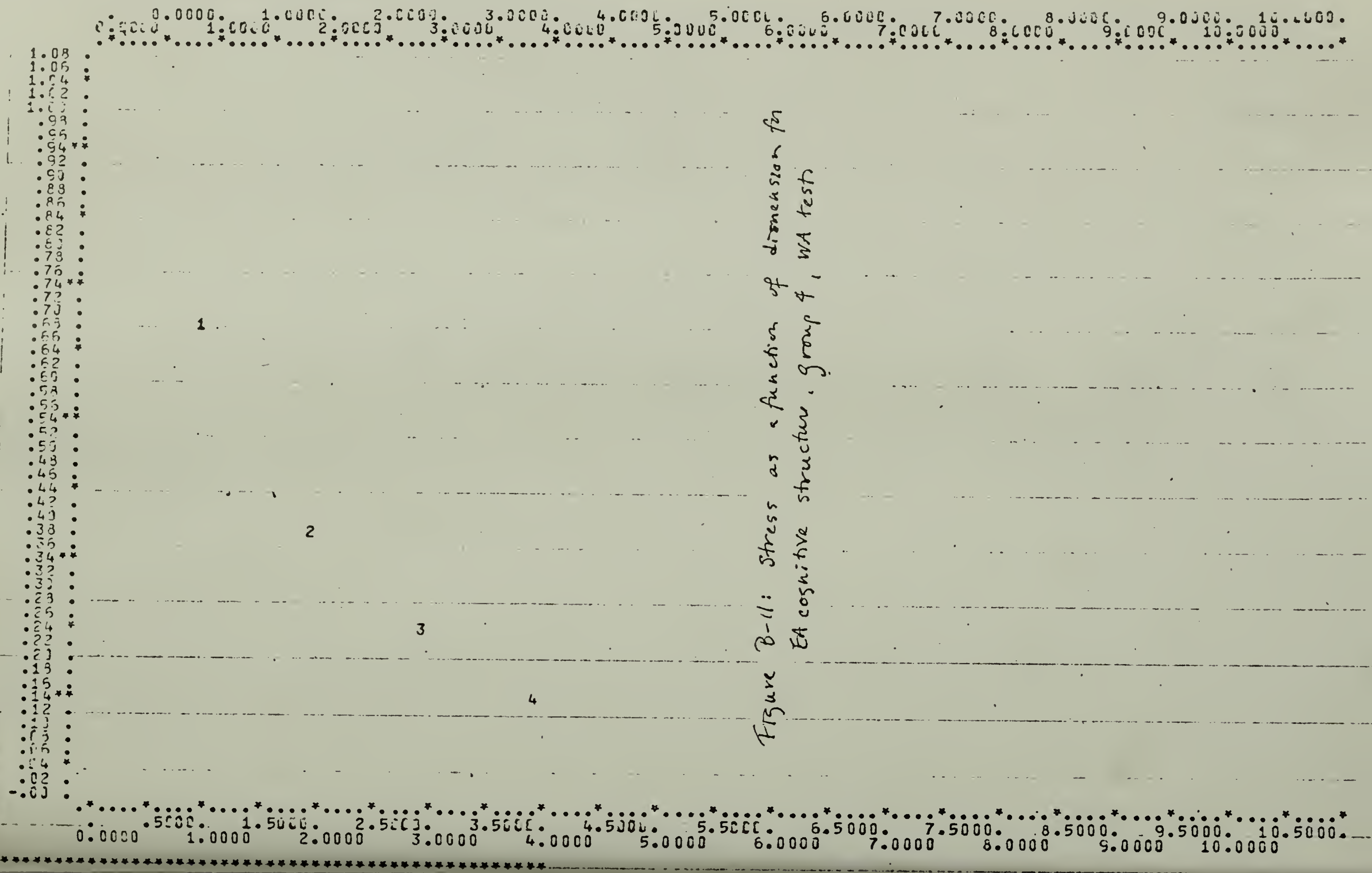


Figure B-11: Stress as a function of dimension for EA cognitive structure, group 4, WA test

PLOT OF STRESS VERSUS DIMENSION ST DISTANCE, ST/EA(1)

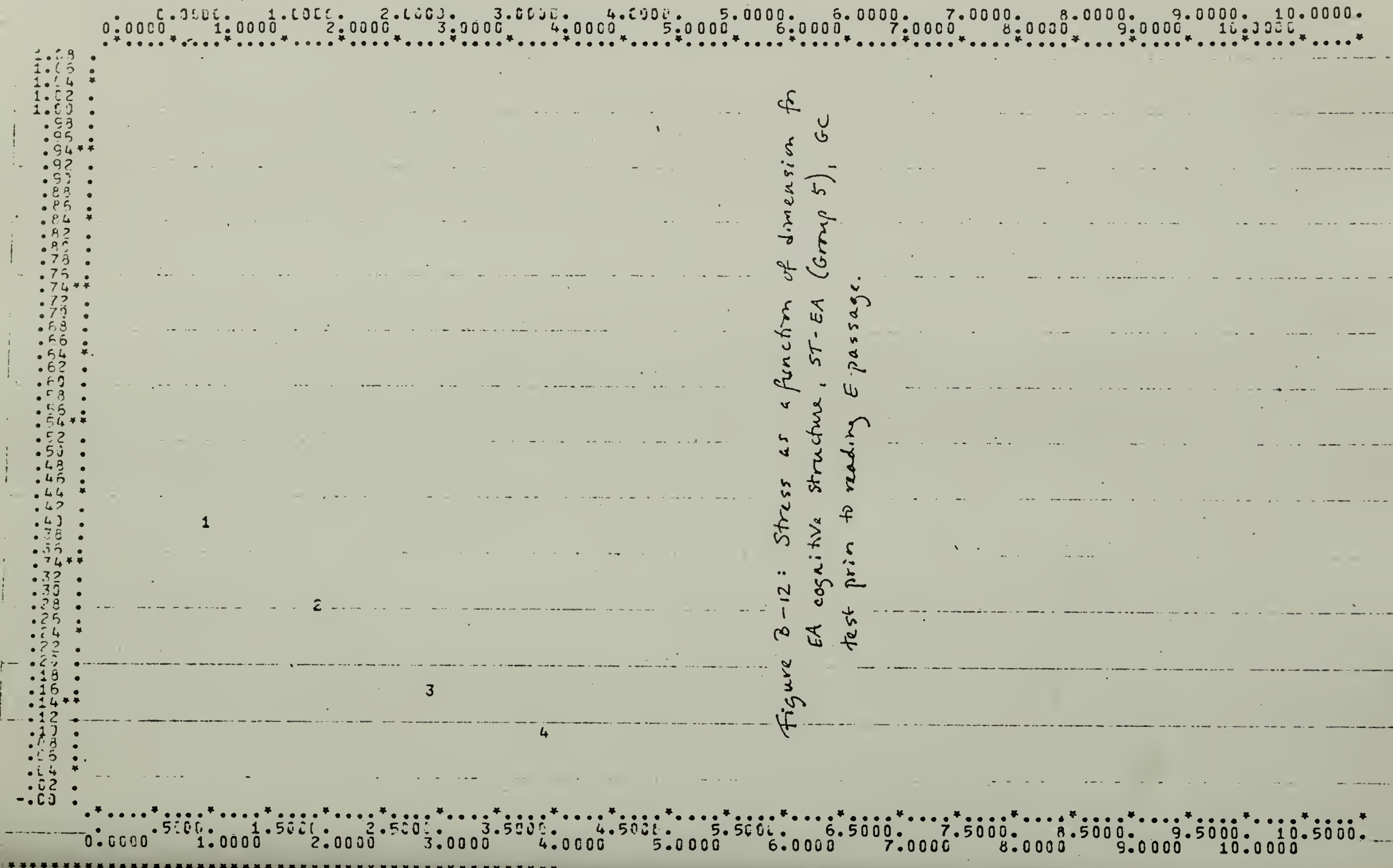


Figure B-12: Stress as a function of dimension for EA cognitive structure, ST-EA (Group 5), GC test prior to reading E passage.

PLOT OF STRESS VERSUS DIMENSION EA RELATEDNESS, ST/EA(1)

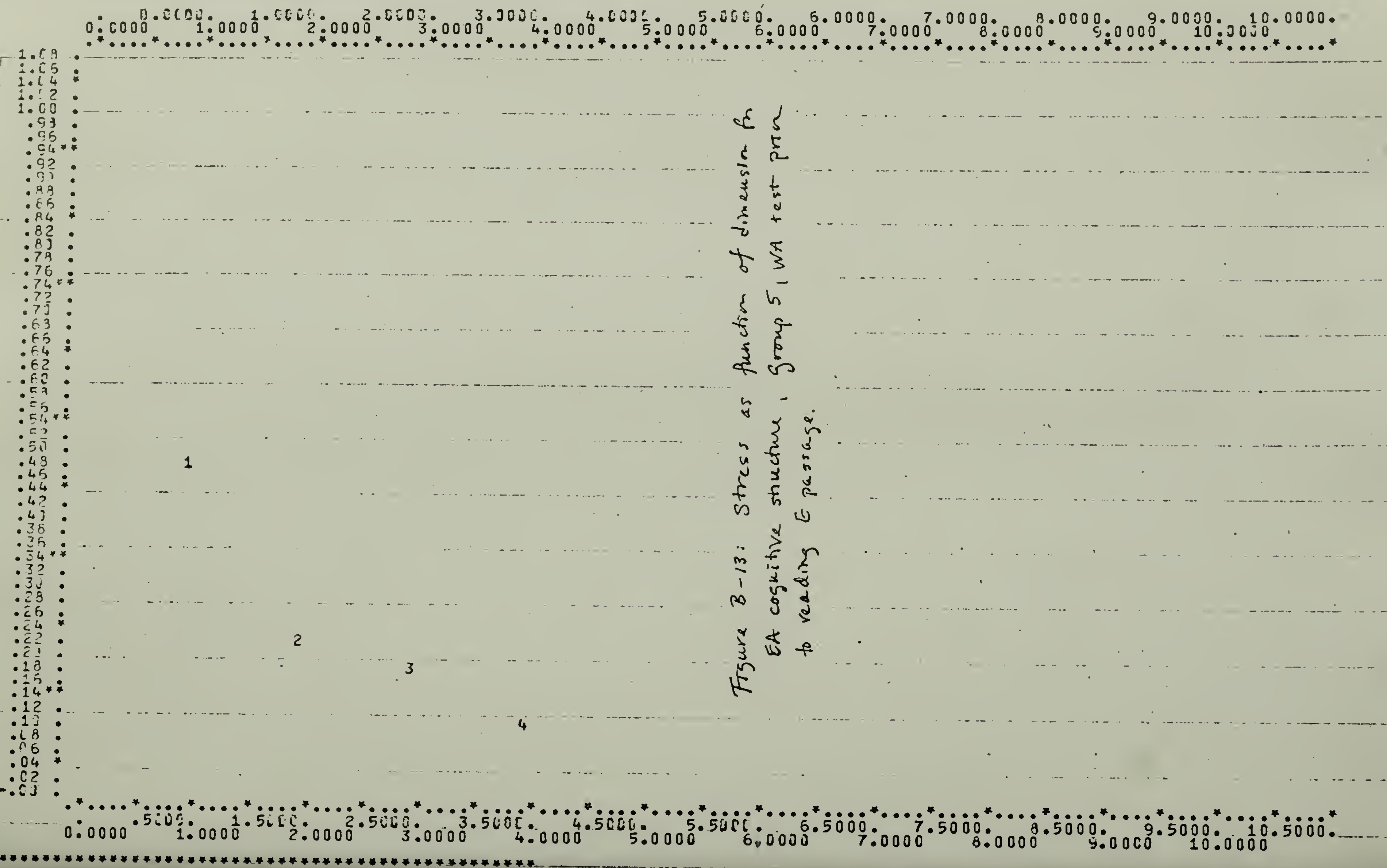


Figure B-13: Stress as function of dimension for EA cognitive structure, Group 5, WA test prior to reading E passage.

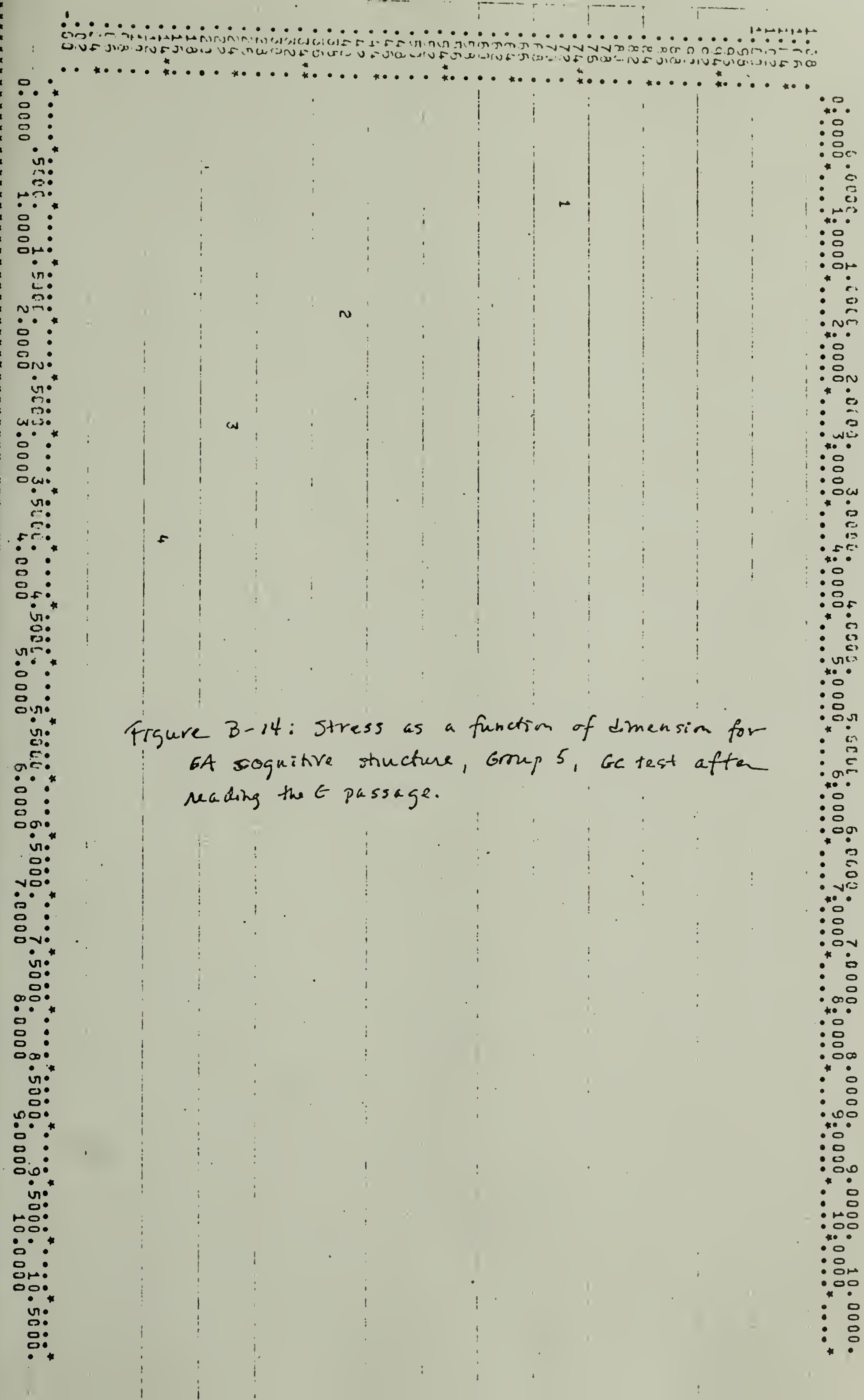


Figure B-14: Stress as a function of dimension for EA cognitive structure, Group 5, GC test after reading the E passage.

PLOT OF STRESS VERSUS DIMENSION EA RELATEDNESS, ST/EA(2)

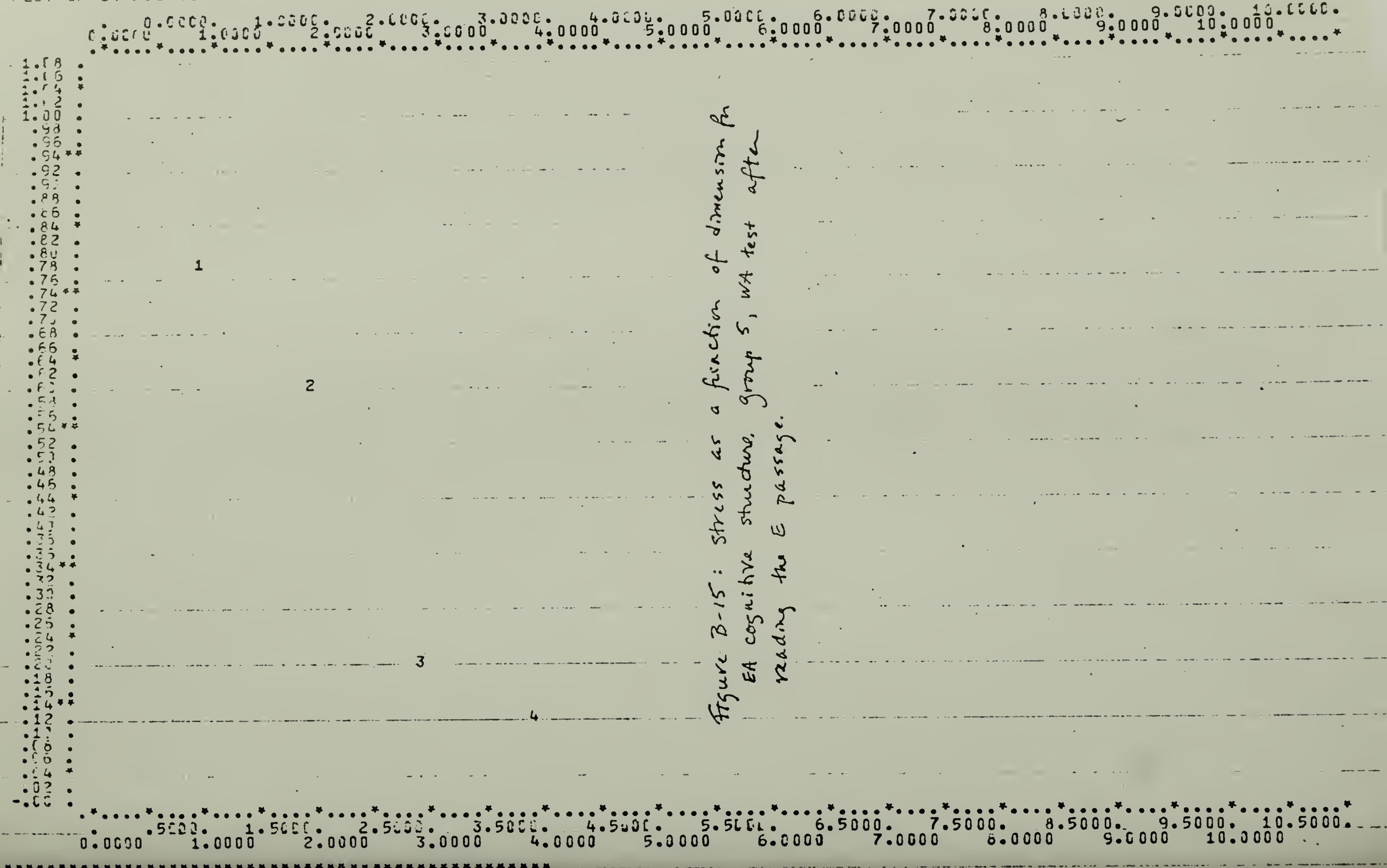


Figure B-15: stress as a function of dimension for EA cognitive structure, group 5, WA test after reading the E passage.

PLOT OF STRESS VERSUS DIMENSION HC DISTANCE, HC/EA(U)

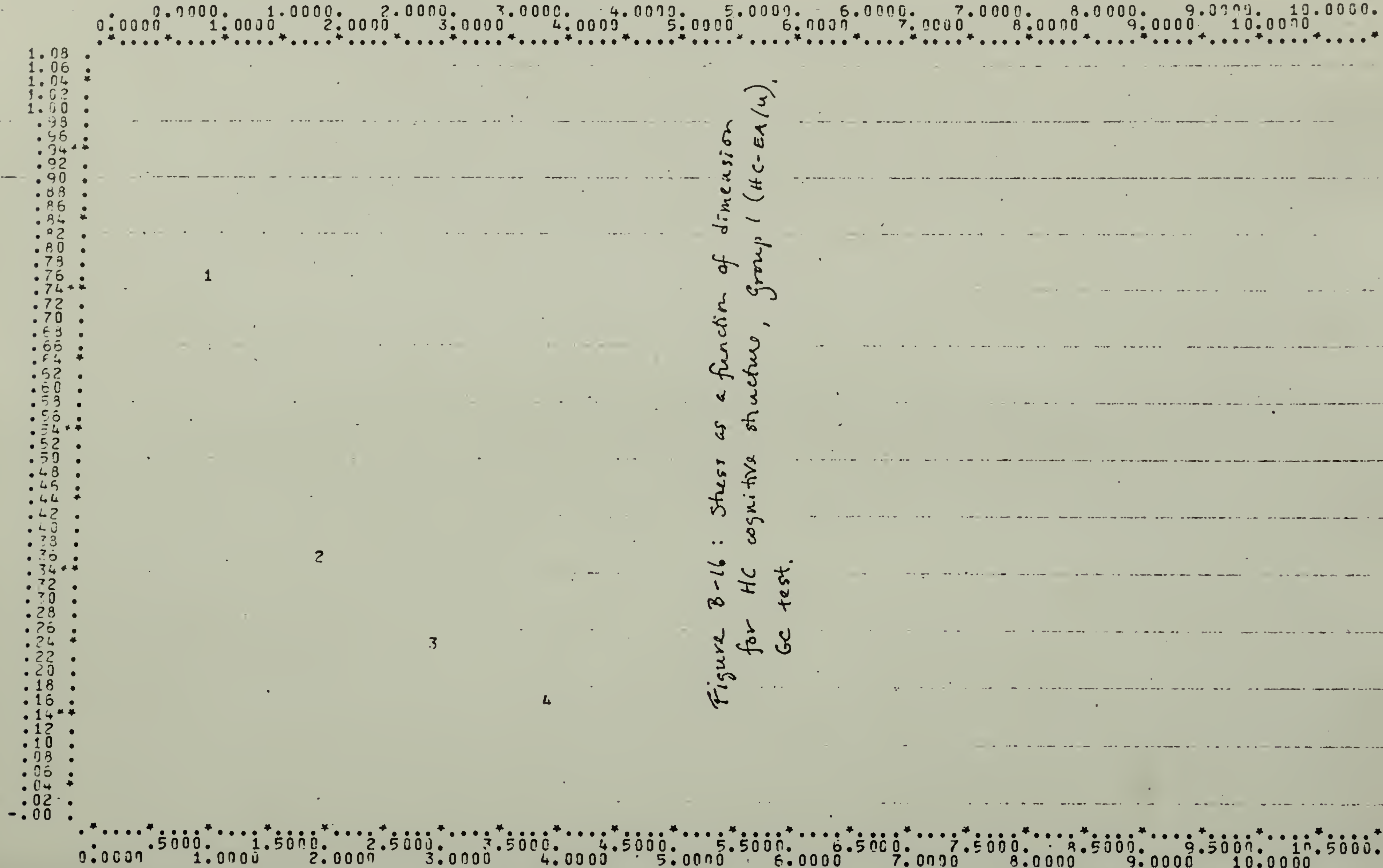


Figure B-16: Stress as a function of dimension for HC cognitive structure, Group 1 (HC-EA/u), GC test.

PLOT OF STRESS VERSUS DIMENSION HC RELATEDNESS, HC/EA(U)

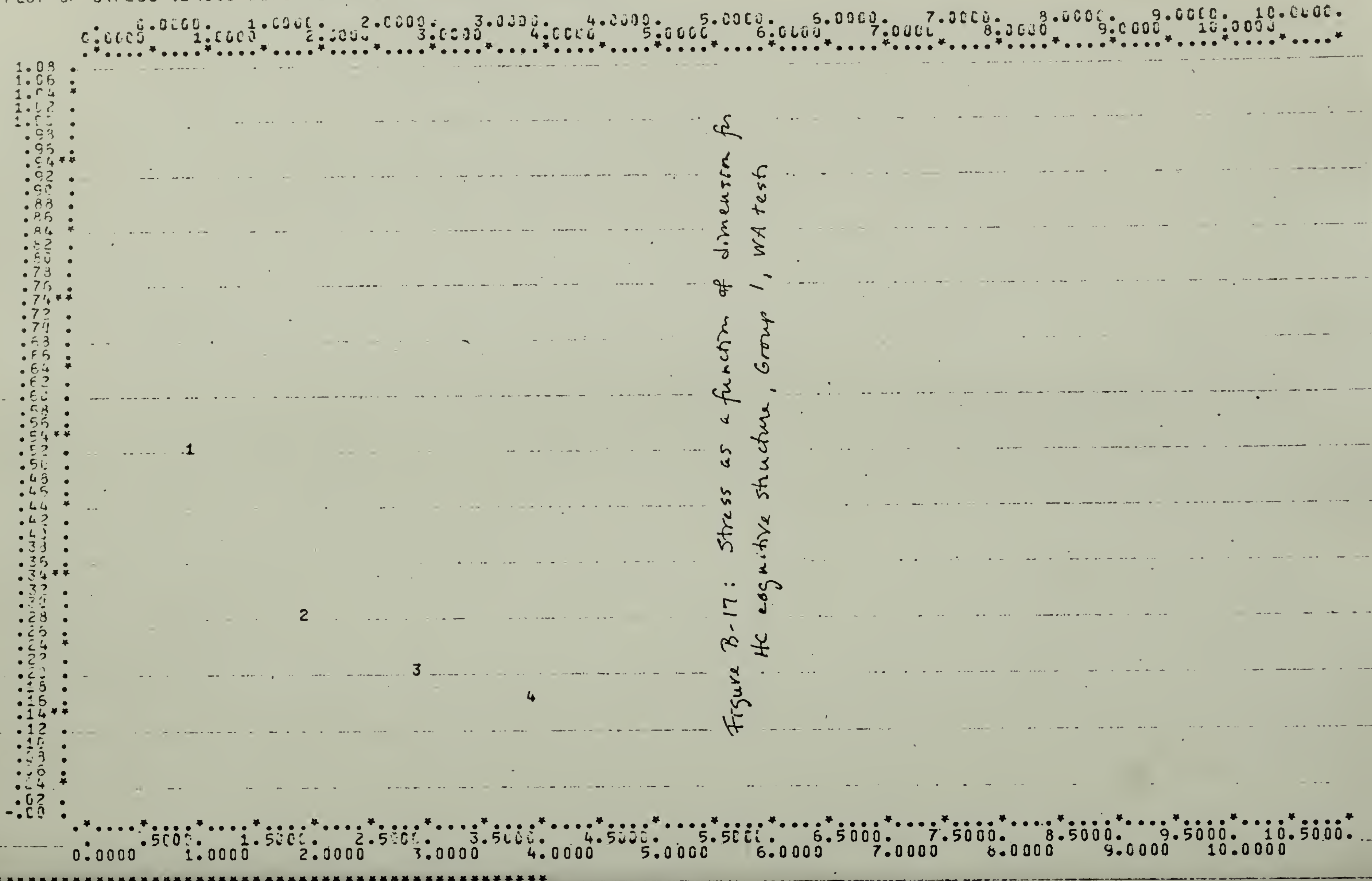


Figure B-17: Stress as a function of dimension for HC cognitive structure, Group 1, WA tests

PLOT OF STRESS VERSUS DIMENSION HC DISTANCE, HC/EA

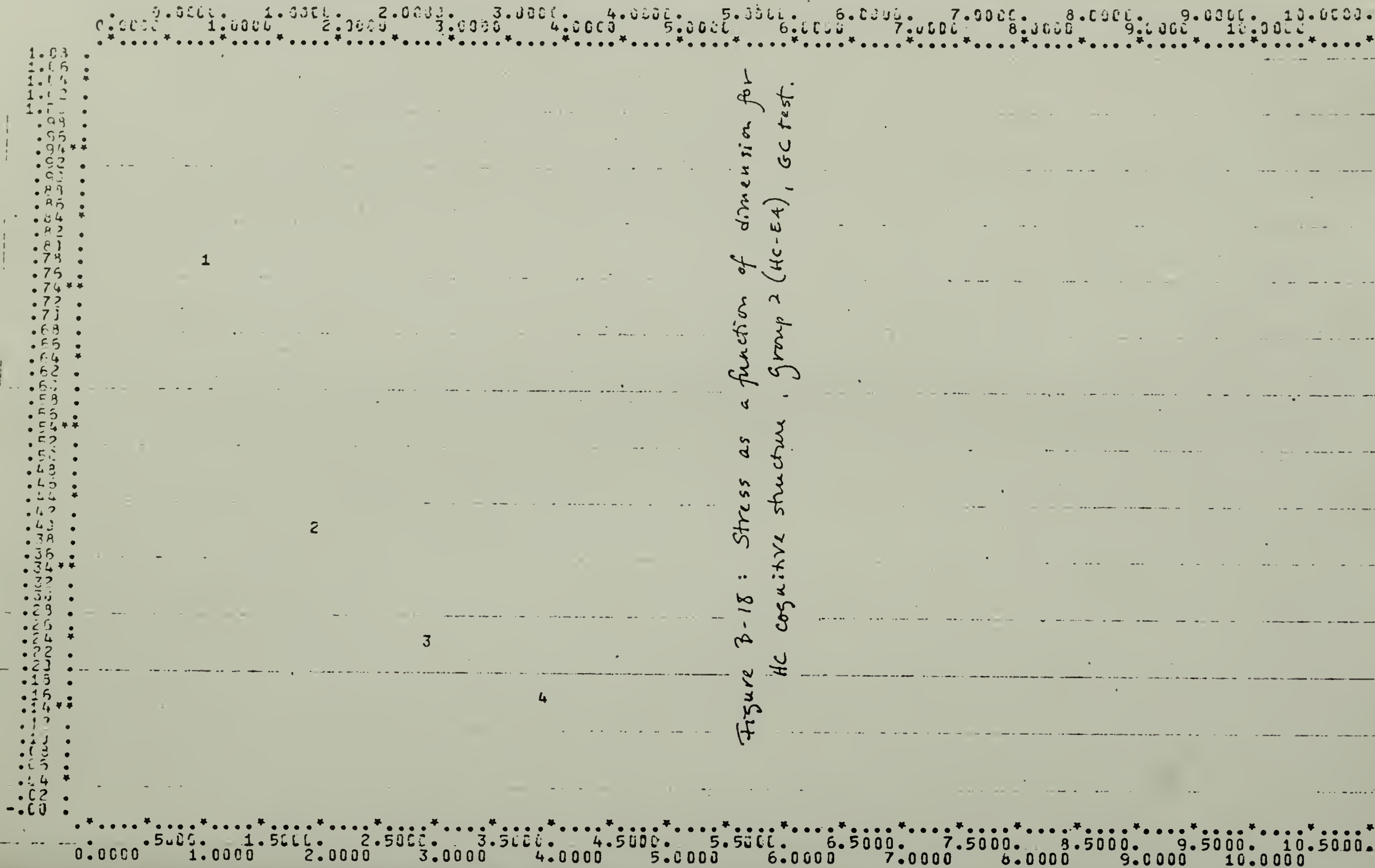


Figure 3-18: Stress as a function of dimension for HC cognitive structure, Group 2 (HC-EA), GC test.

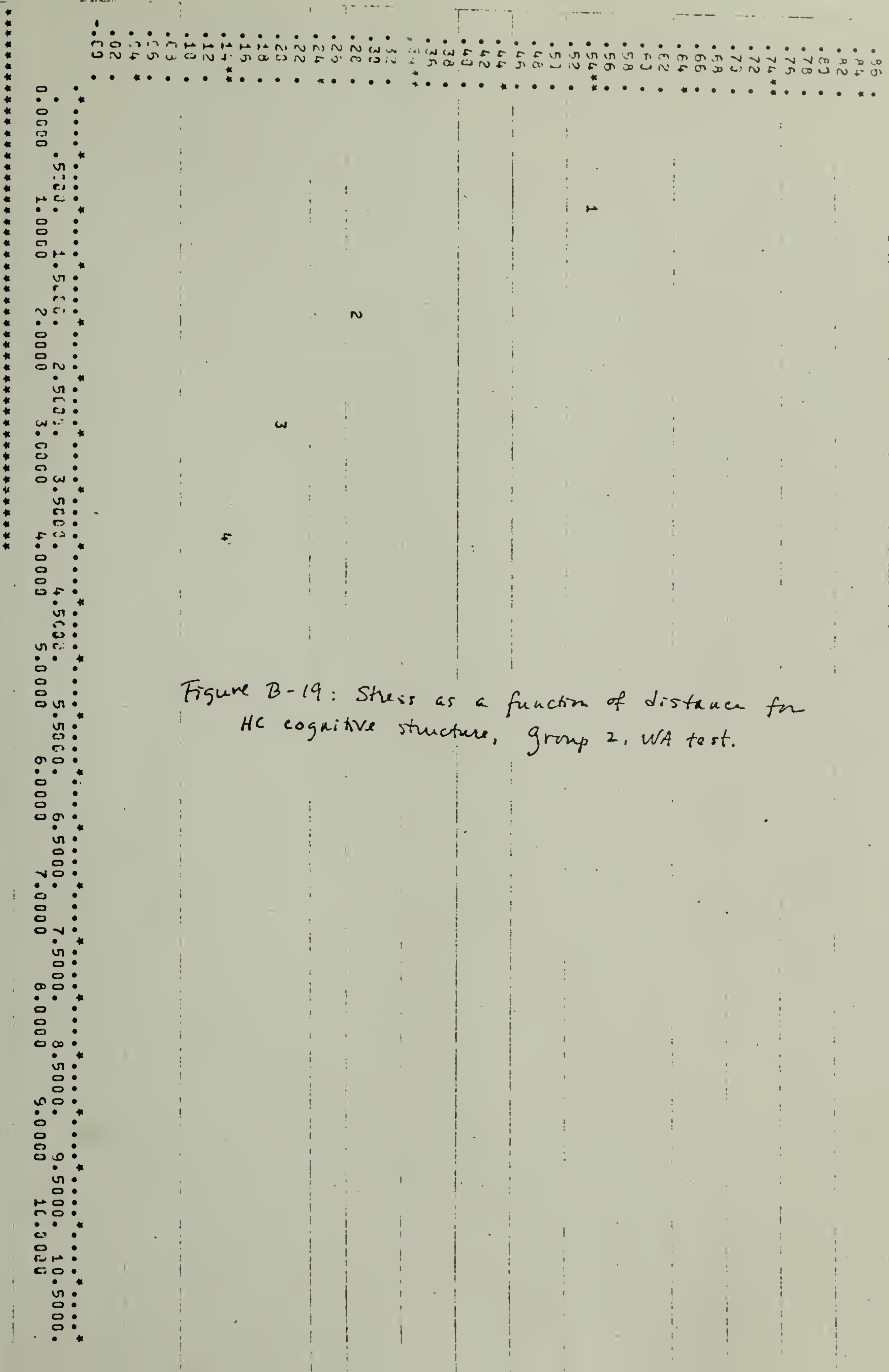


Figure B-19: Stress as a function of distance for HC cognitive structure, group 2, WA test.

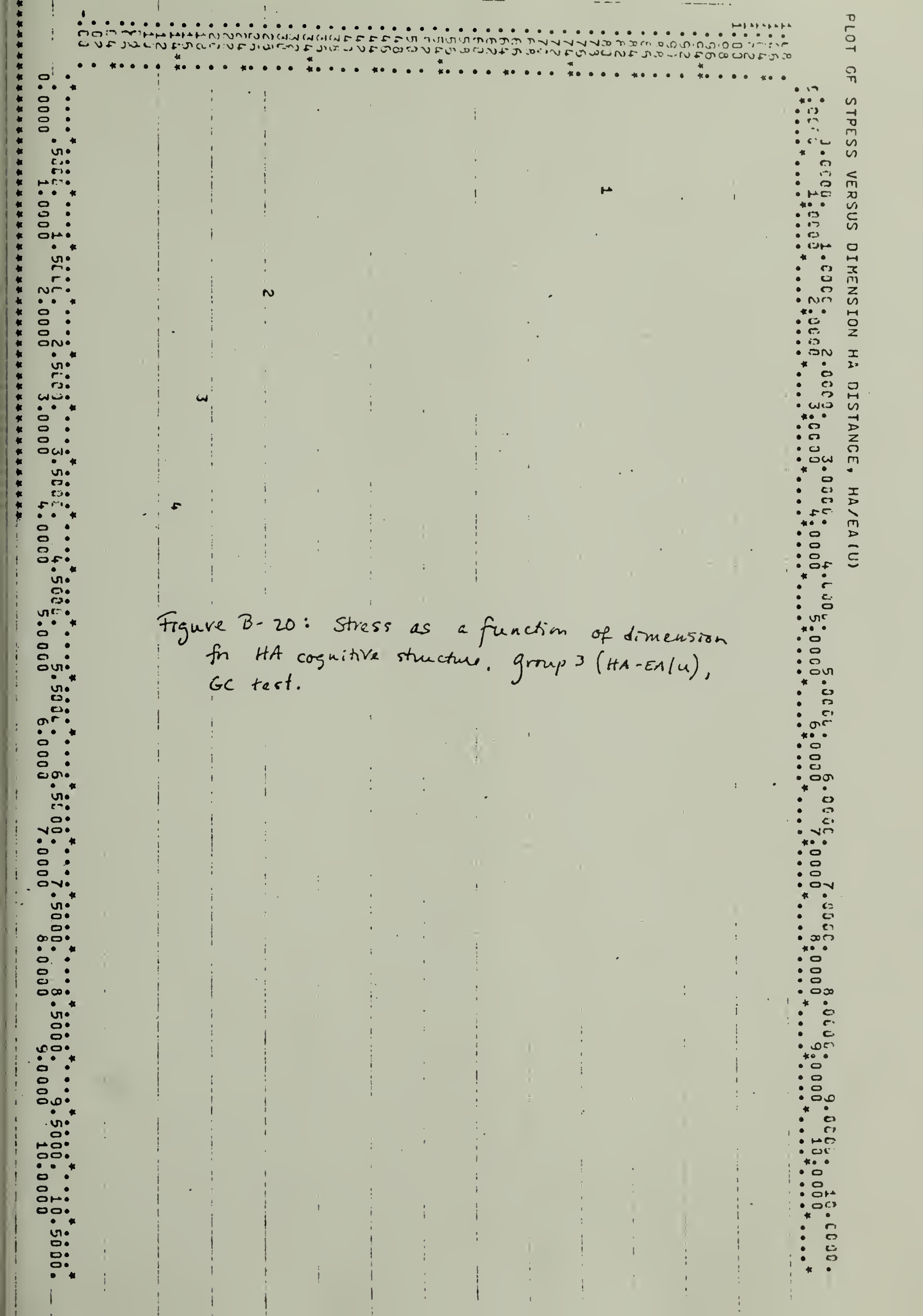


Figure B-20: Stress as a function of dimension for HA cognitive structure. group 3 (HA-EA/u), GC test.

PLOT OF STRESS VERSUS DIMENSION HA RELATEDNESS, HA/EA(U)

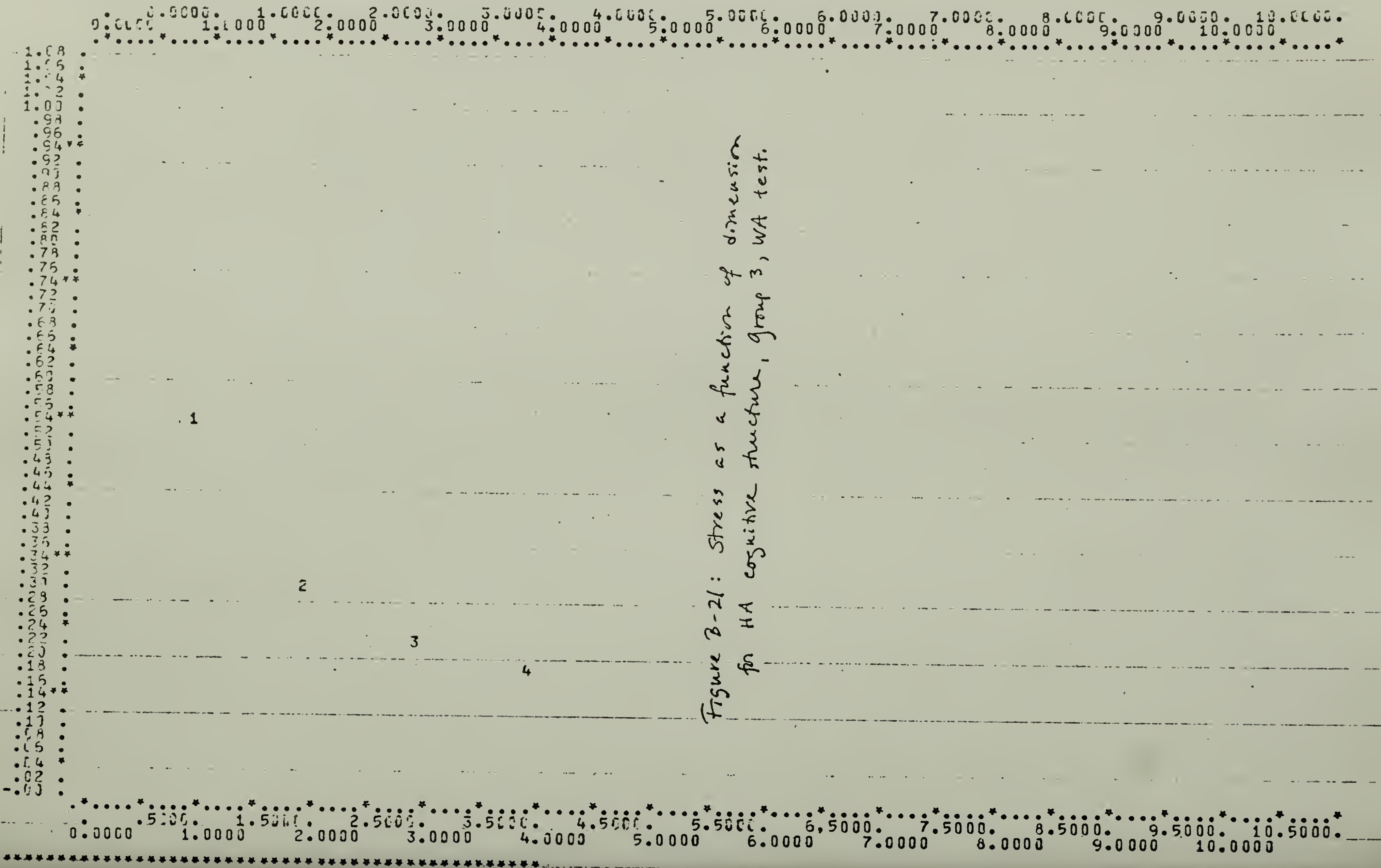


Figure B-21: Stress as a function of dimension for HA cognitive structure, group 3, WA test.

PLOT OF STRESS VERSUS DIMENSION HA DISTANCE, HA/EA

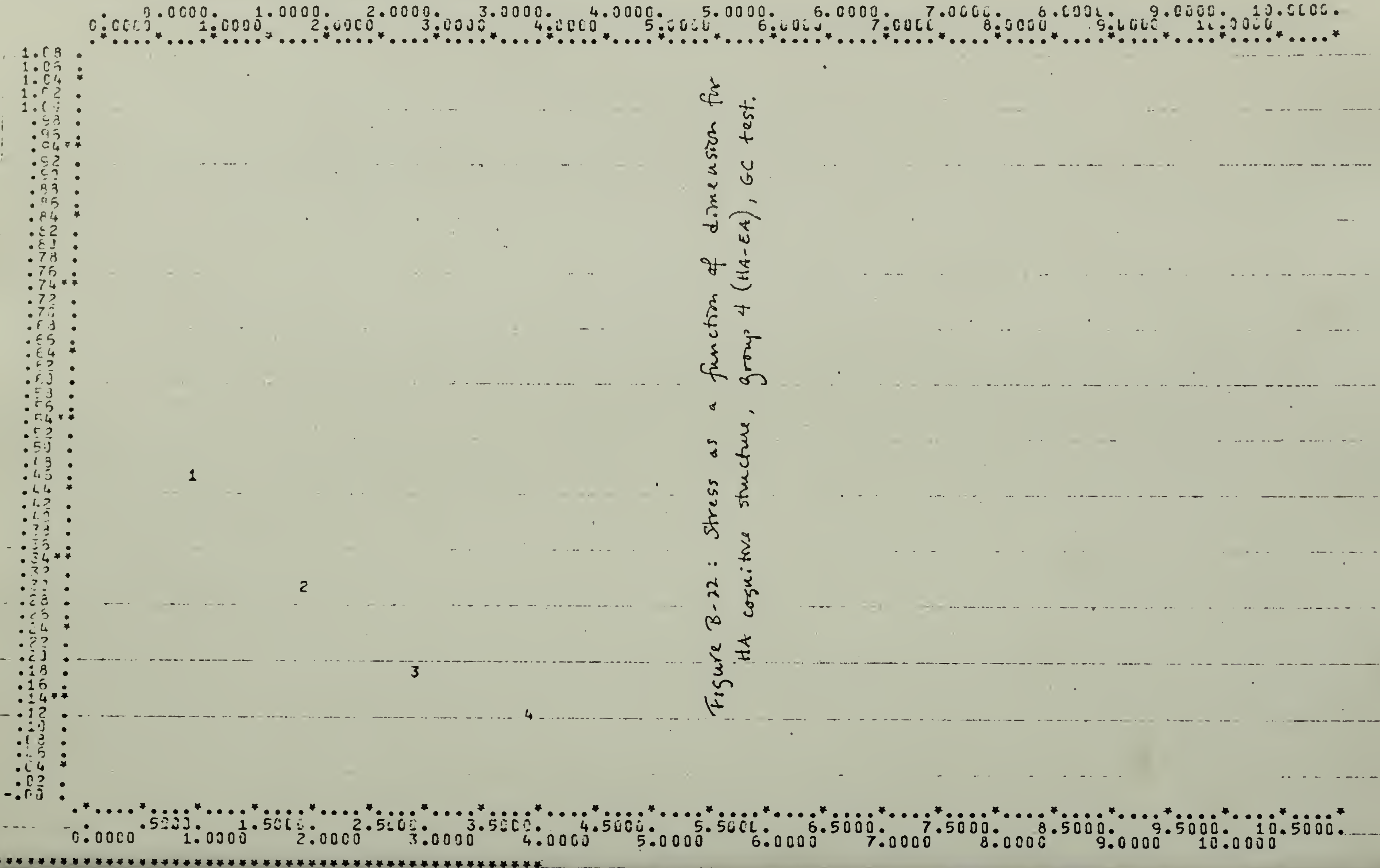


Figure B-22: Stress as a function of dimension for HA cognitive structure, group 4 (HA-EA), GC test.

PLOT OF STRESS VERSUS DIMENSION HA RELATEDNESS, HA/EA

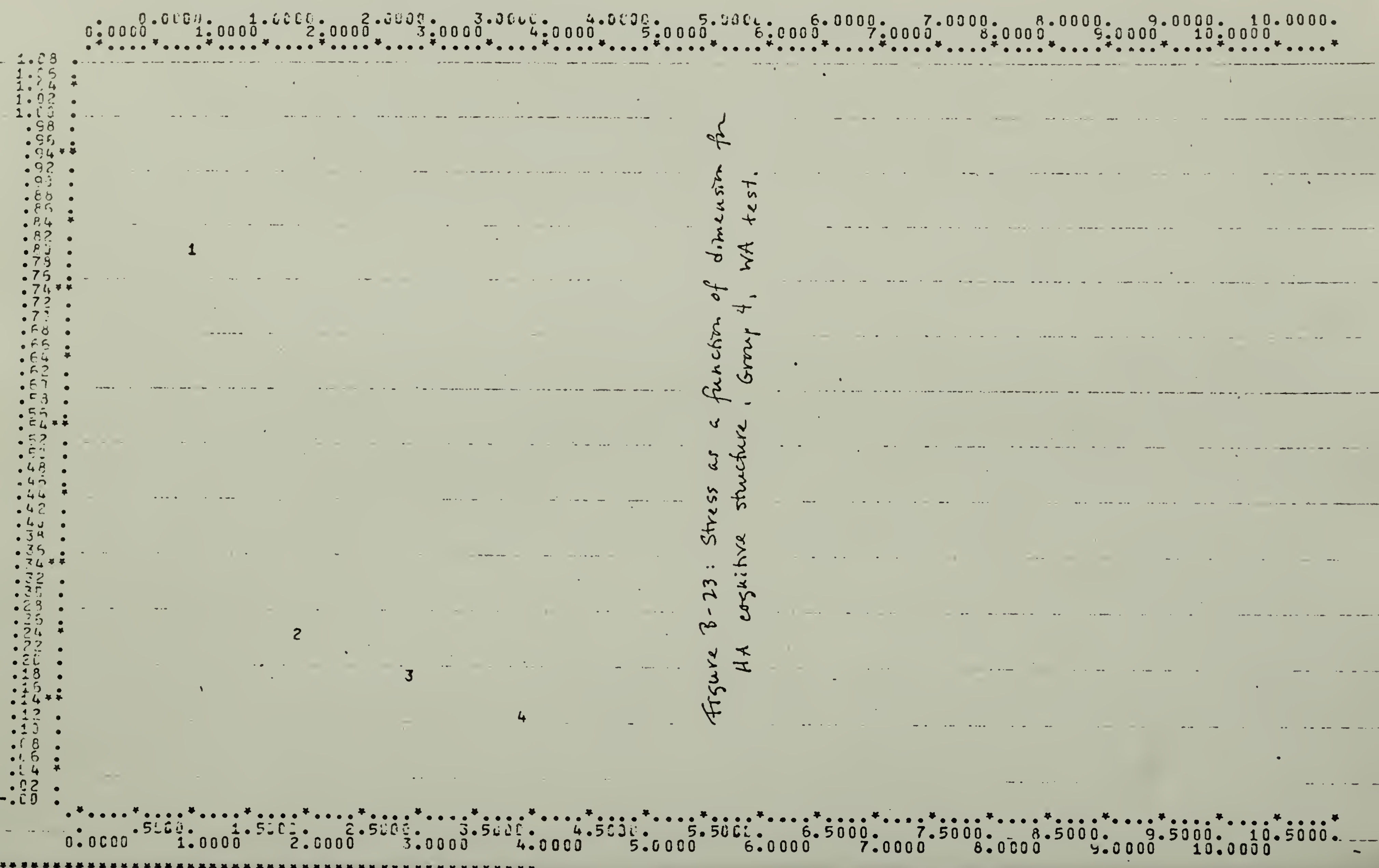


Figure B-23: Stress as a function of dimension for HA cognitive structure, Group 4, WA test.

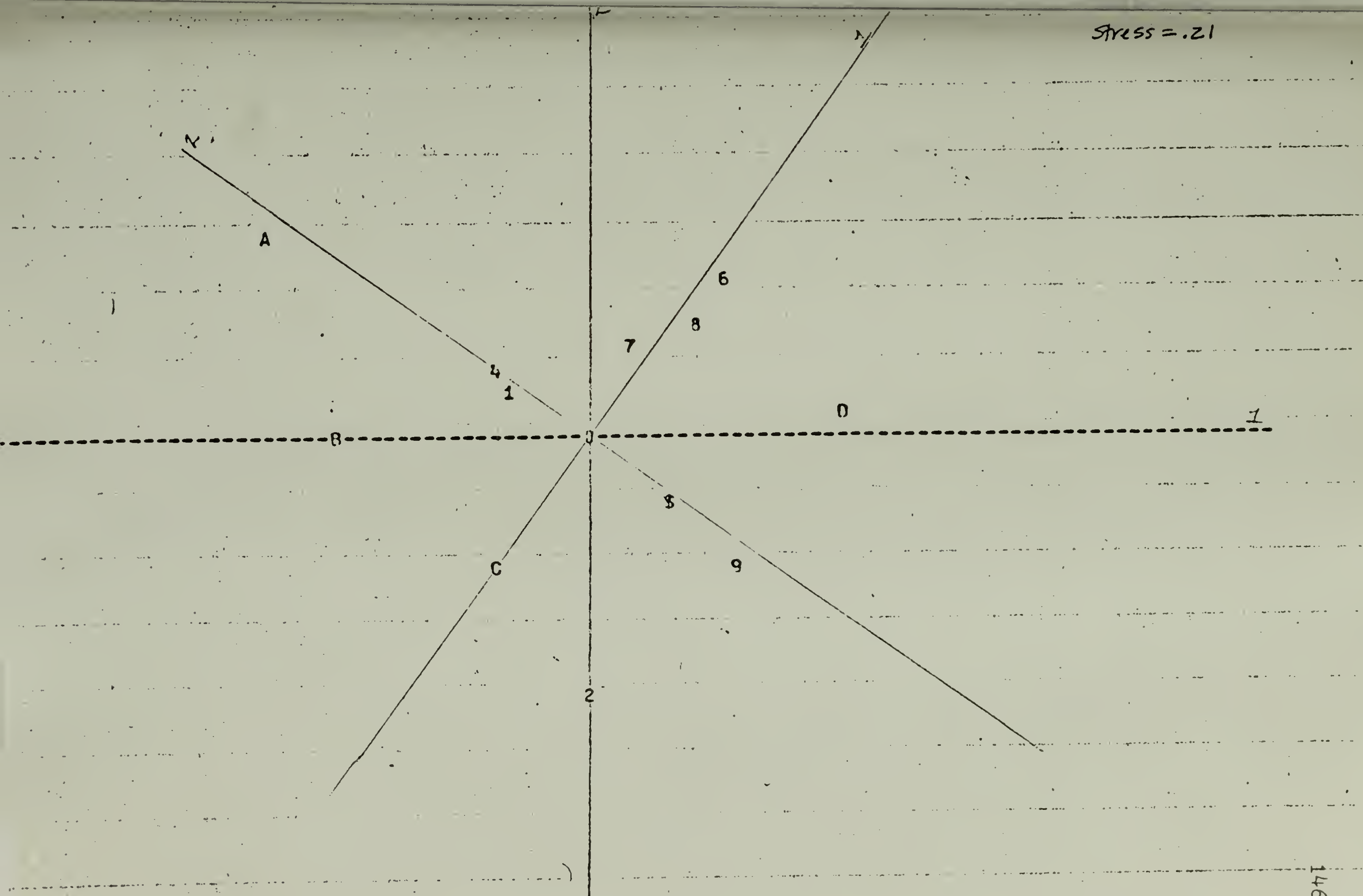


Figure B-24. Multidimensional scaling solution — two space configuration for the content structure of the electrical concepts (abstract).

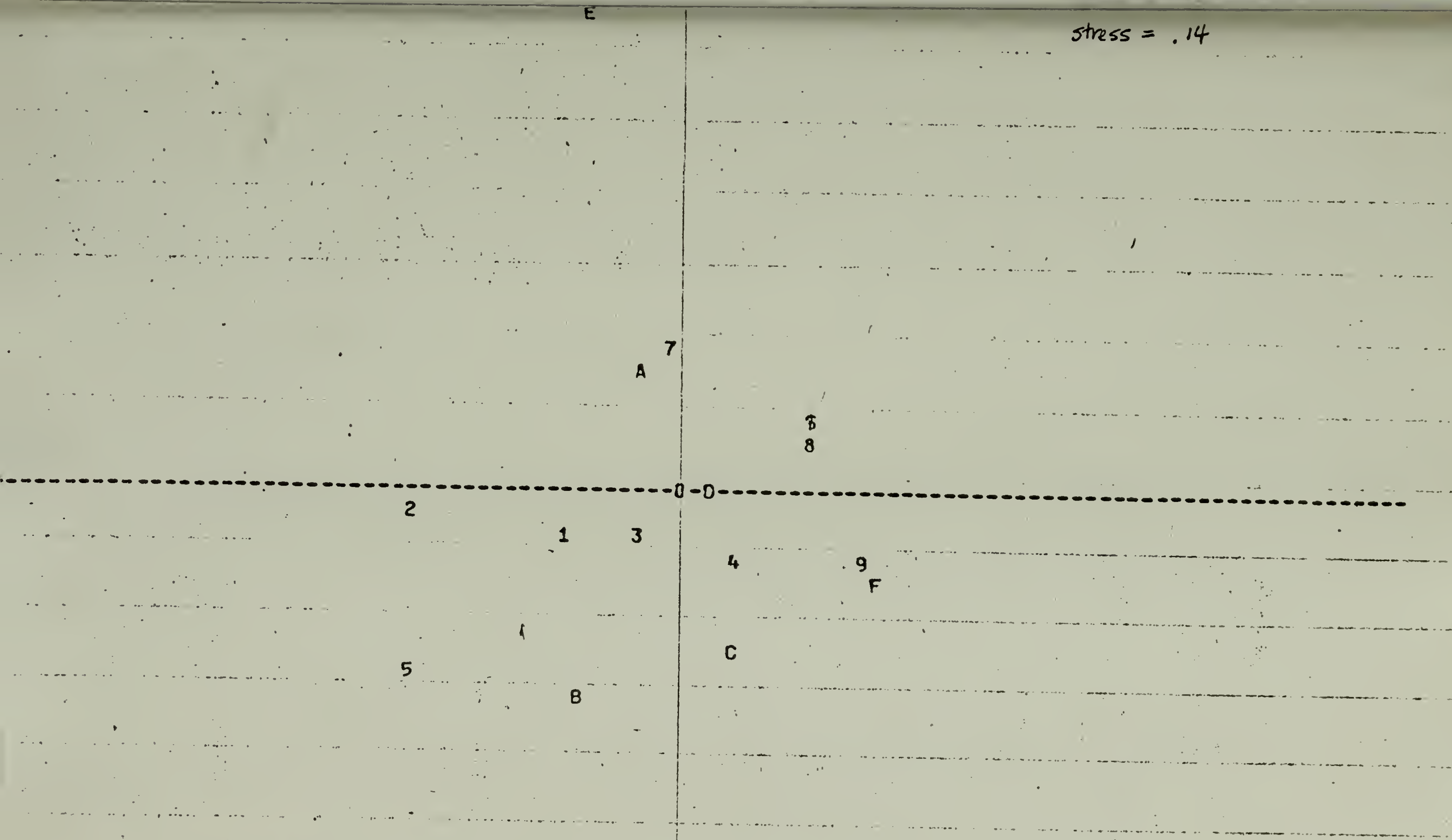


Figure 3-25: Multidimensional Scaling solution — two space configuration for the content structure of the heat flow concepts (concrete).

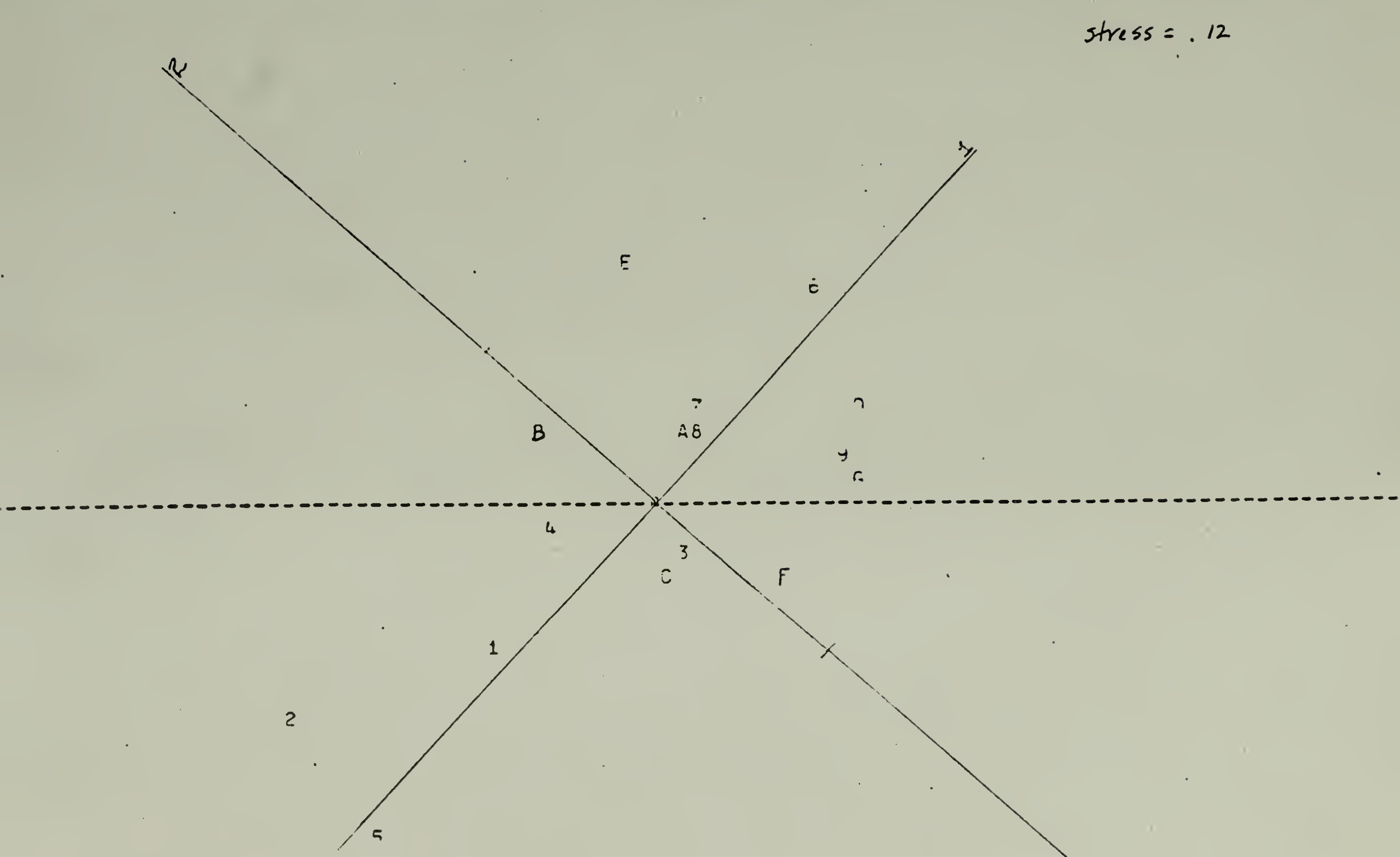


Figure 3-26: Multidimensional scaling solution — two space configuration for the content structure of the heat flow concepts (abstract).

TWO-SPACE CONFIGURATION FOR EA RELATEDNESS, HC/EA(U)
STRESS = .2925

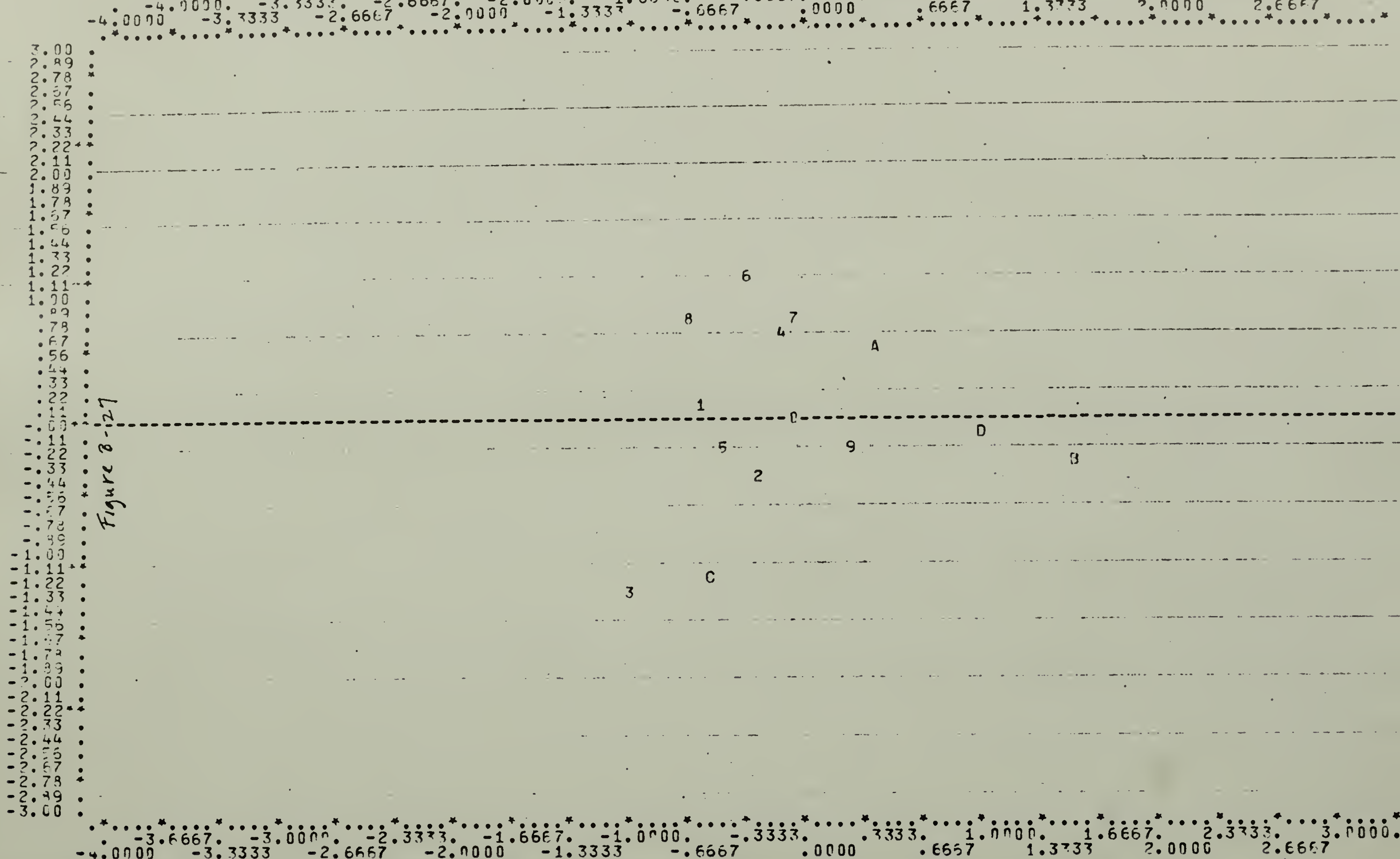


Figure 8-27

TWO SPACE CONFIGURATION FOR EA DISTANCE, HC/EA(U)
STRESS = .3475

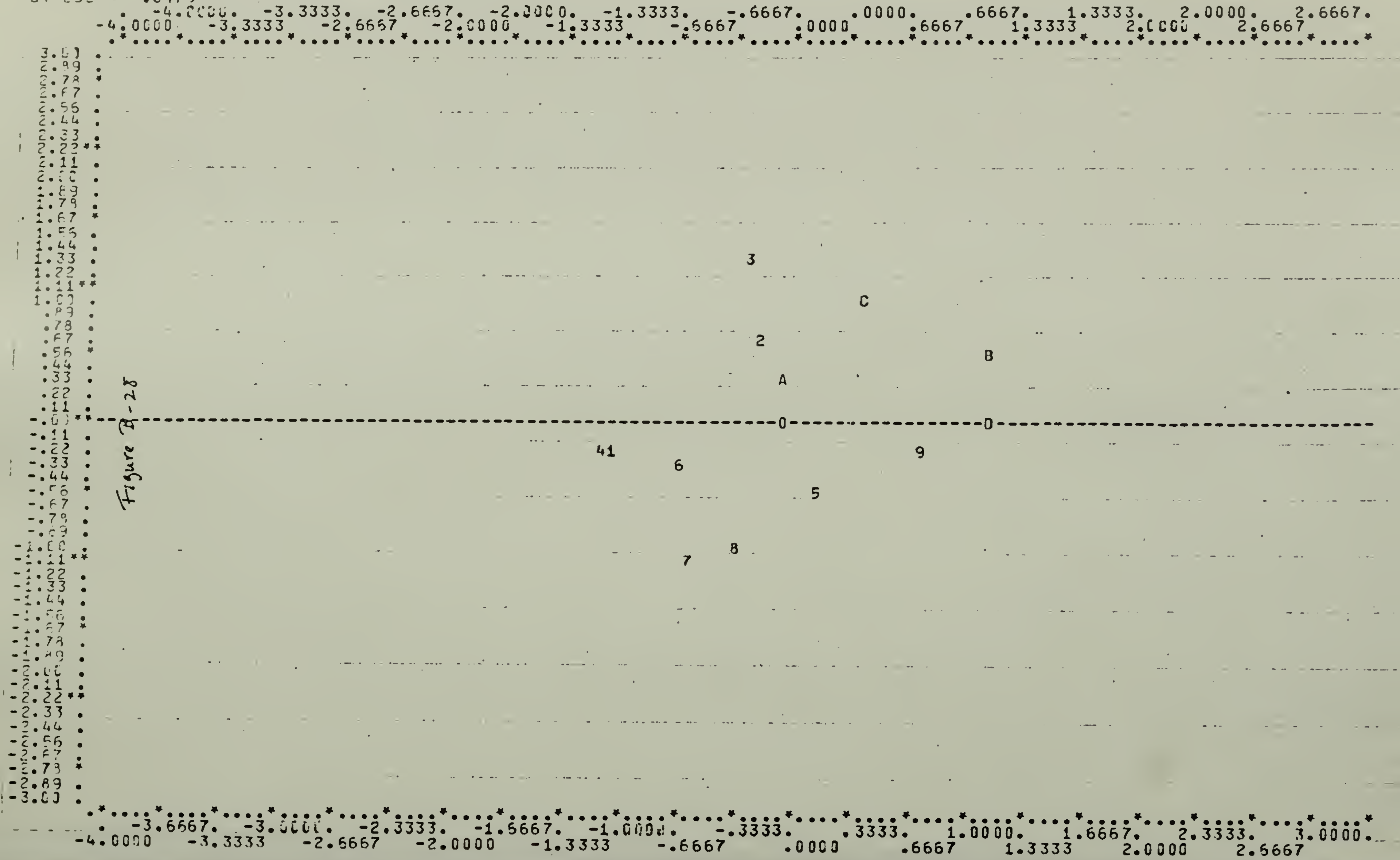


Figure B-28

TWO SPACE CONFIGURATION FOR FA RELATEDNESS, HC/EA
STRESS = .2818

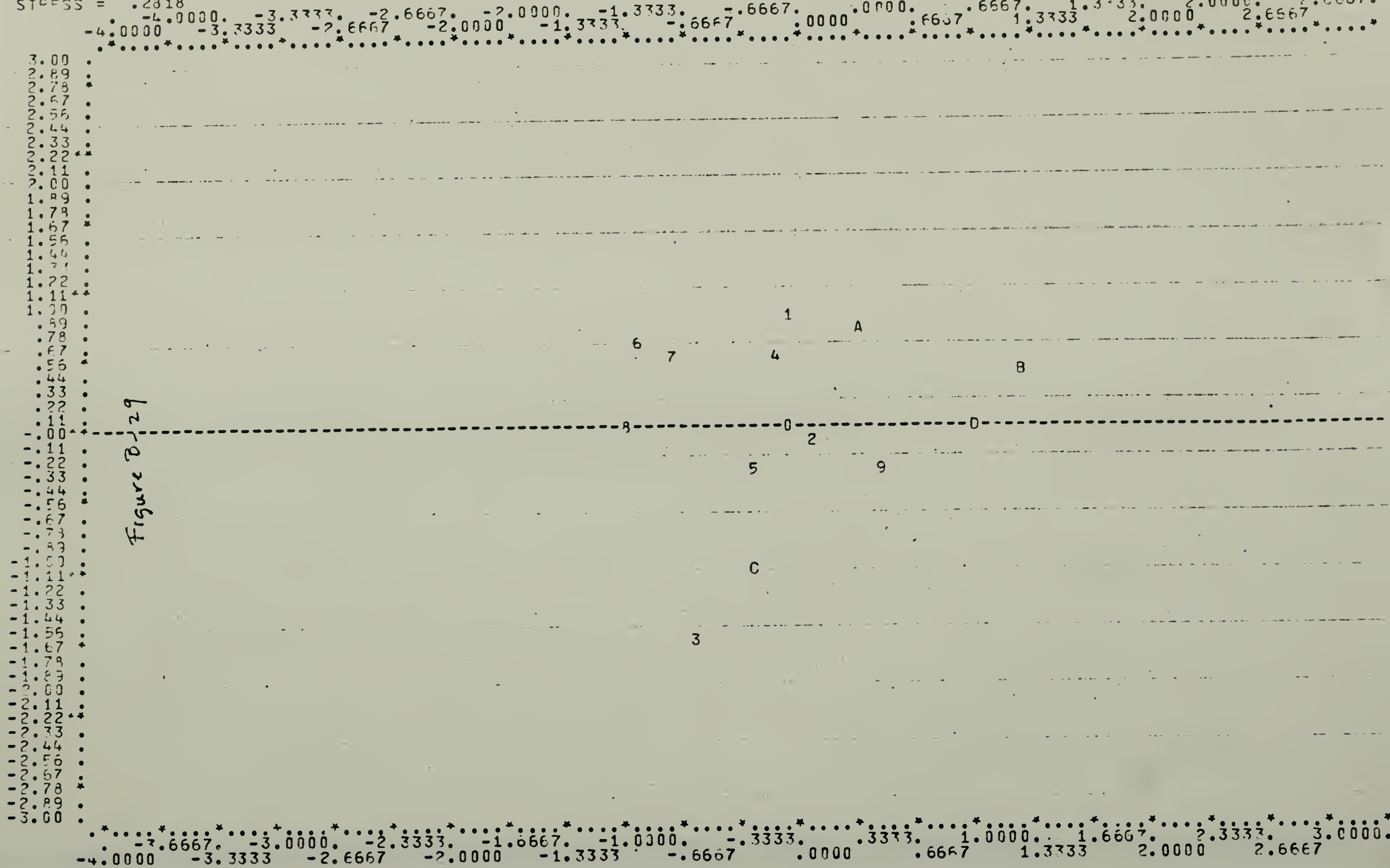


Figure B-29

TWO SPACE CONFIGURATION FOR EA DISTANCE, HC/EA
STRESS = .2358

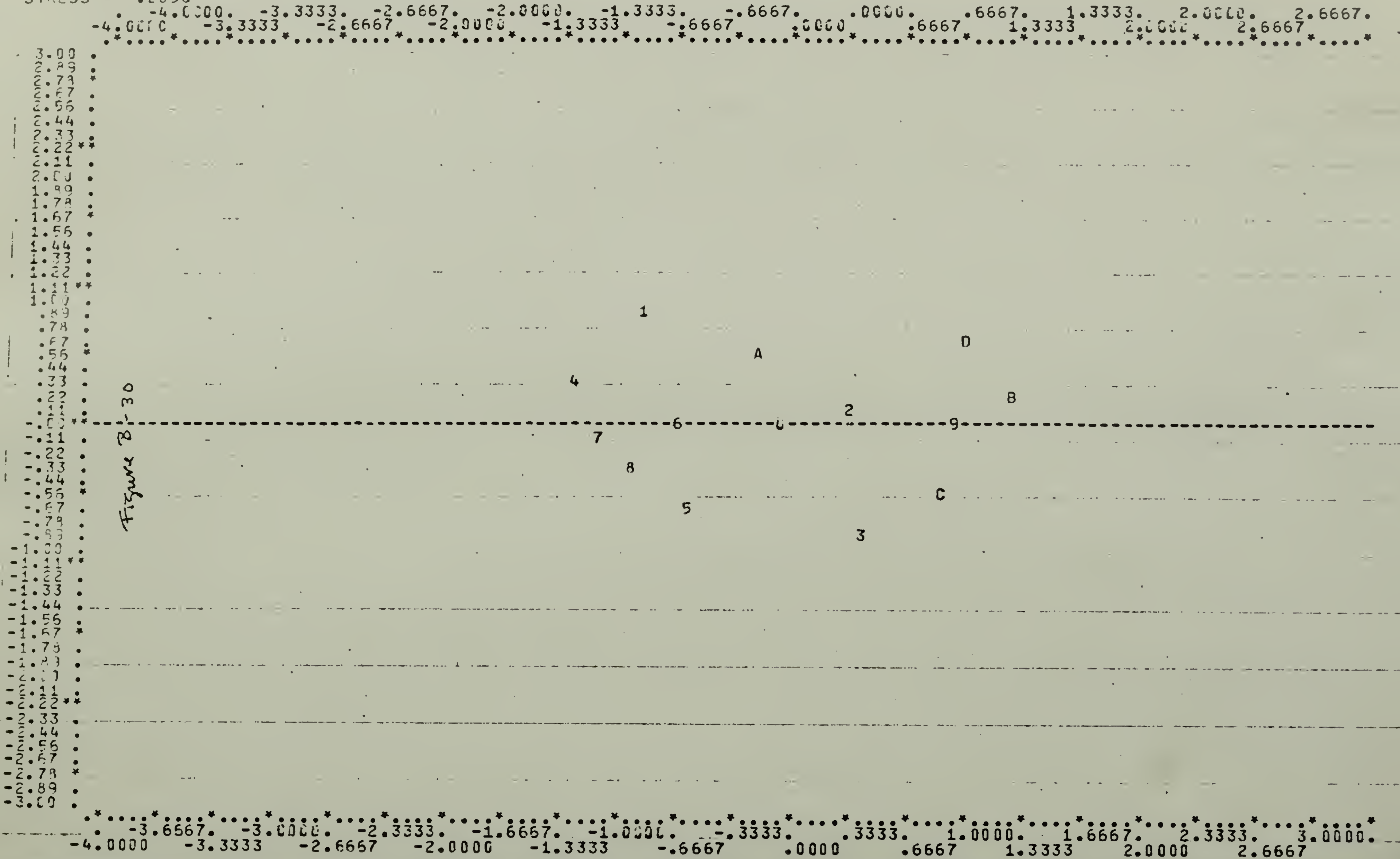


Figure B-30

TWO SPACE CONFIGURATION FOR EA RELATEDNESS, HA/EA(U)
STRESS = .2993

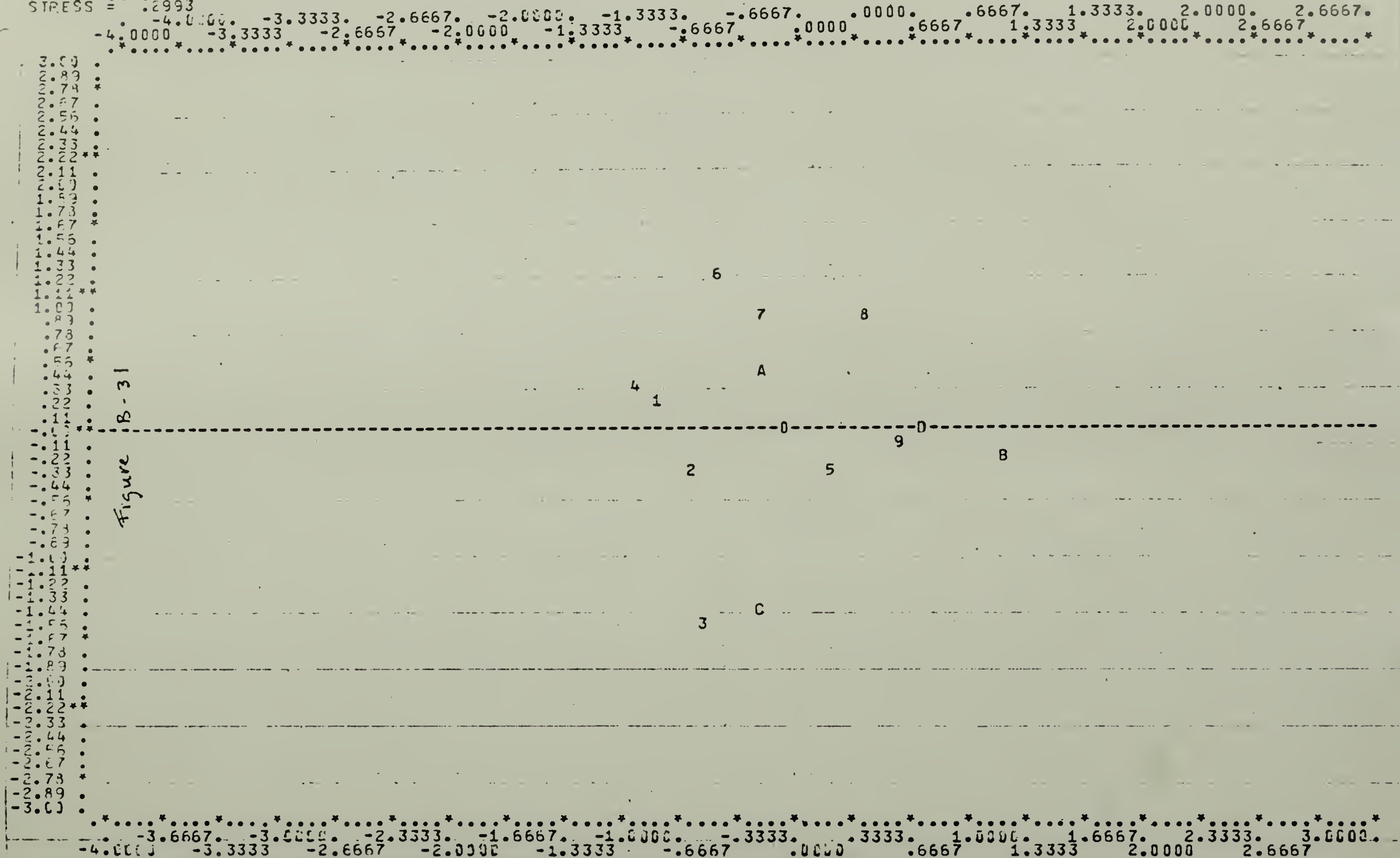


Figure B-31

TWO SPACE CONFIGURATION FOR EA DISTANCE, HA/EA(U)
STRESS = .3665

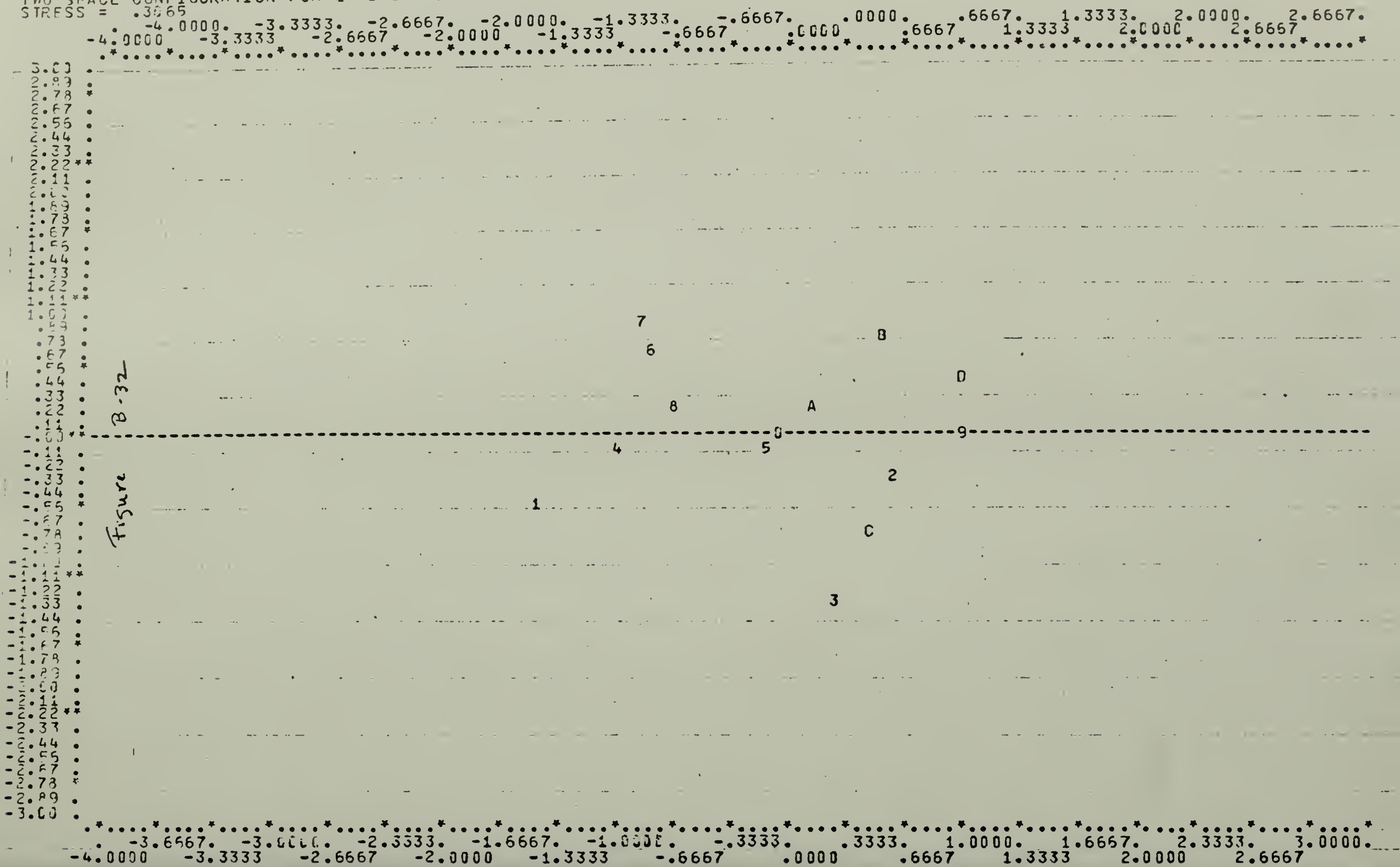


Figure B-32

TWO SPACE CONFIGURATION FOR EA RELATEDNESS, HA/EA
STRESS = .3857

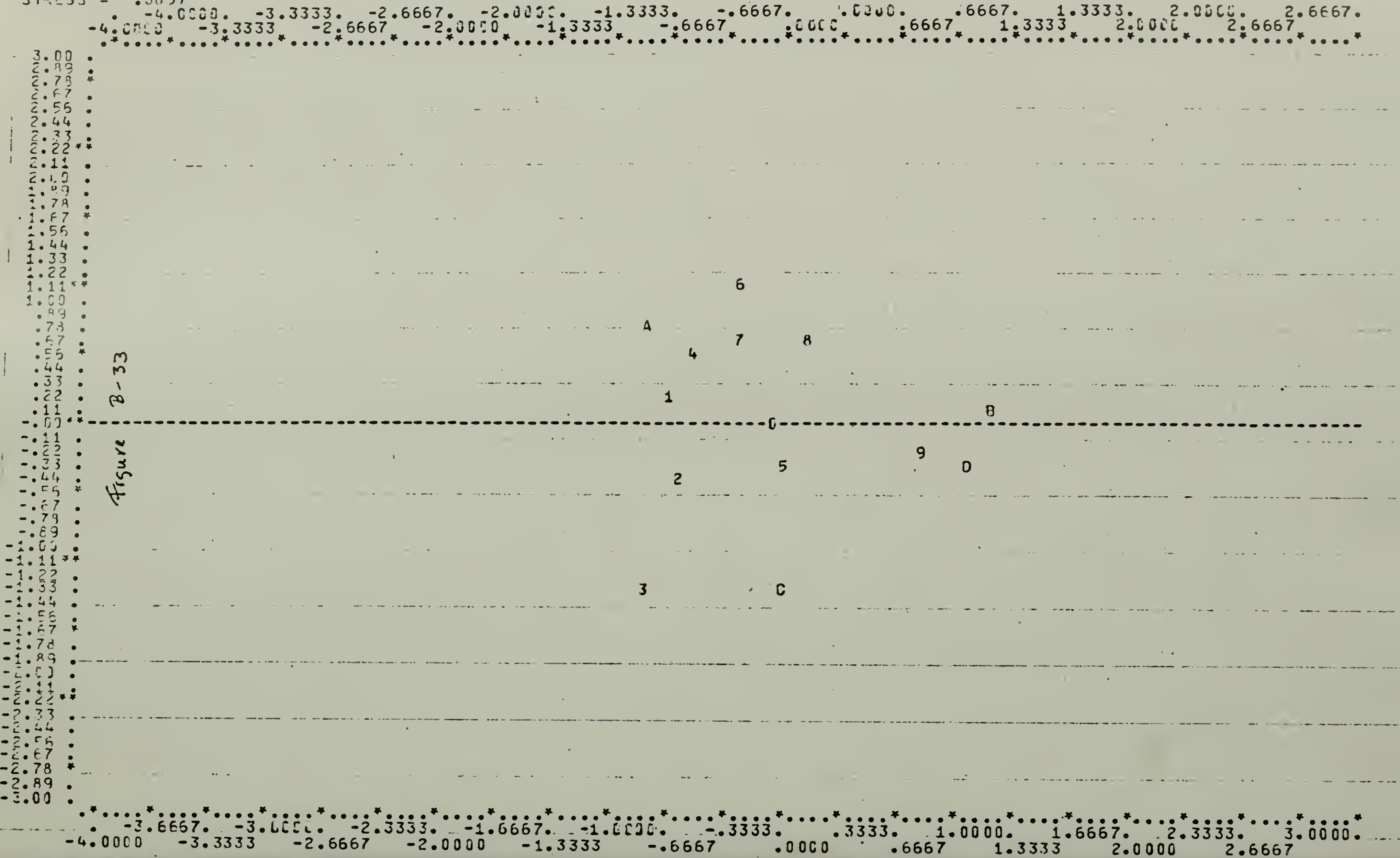


Figure B-33

TWO SPACE CONFIGURATION FOR EA DISTANCE, HA/EA
STRESS = .7434

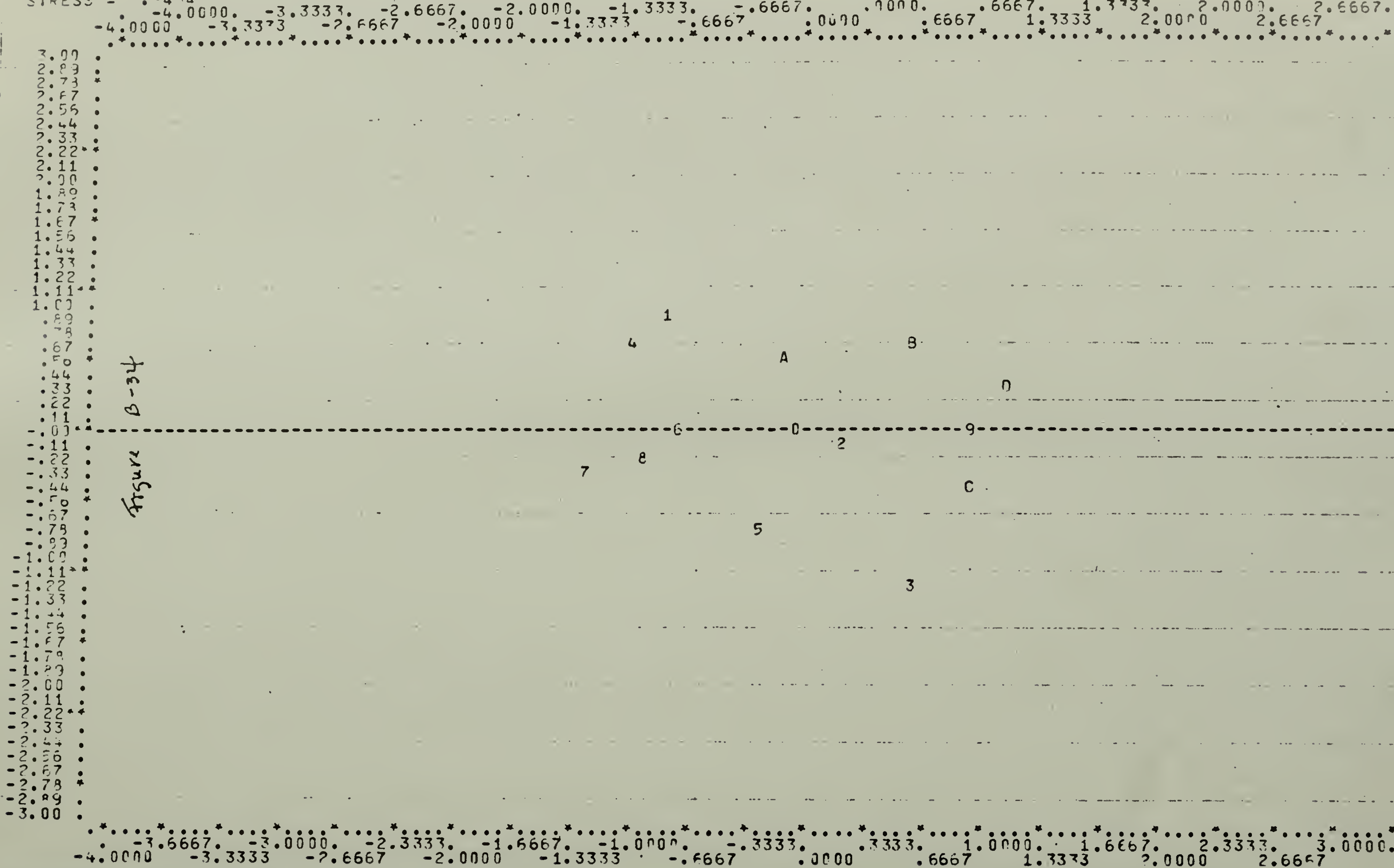


Figure B-34

TWO SPACE CONFIGURATION FOR EA RELATEDNESS, ST/EA(1)
STRESS = .2139

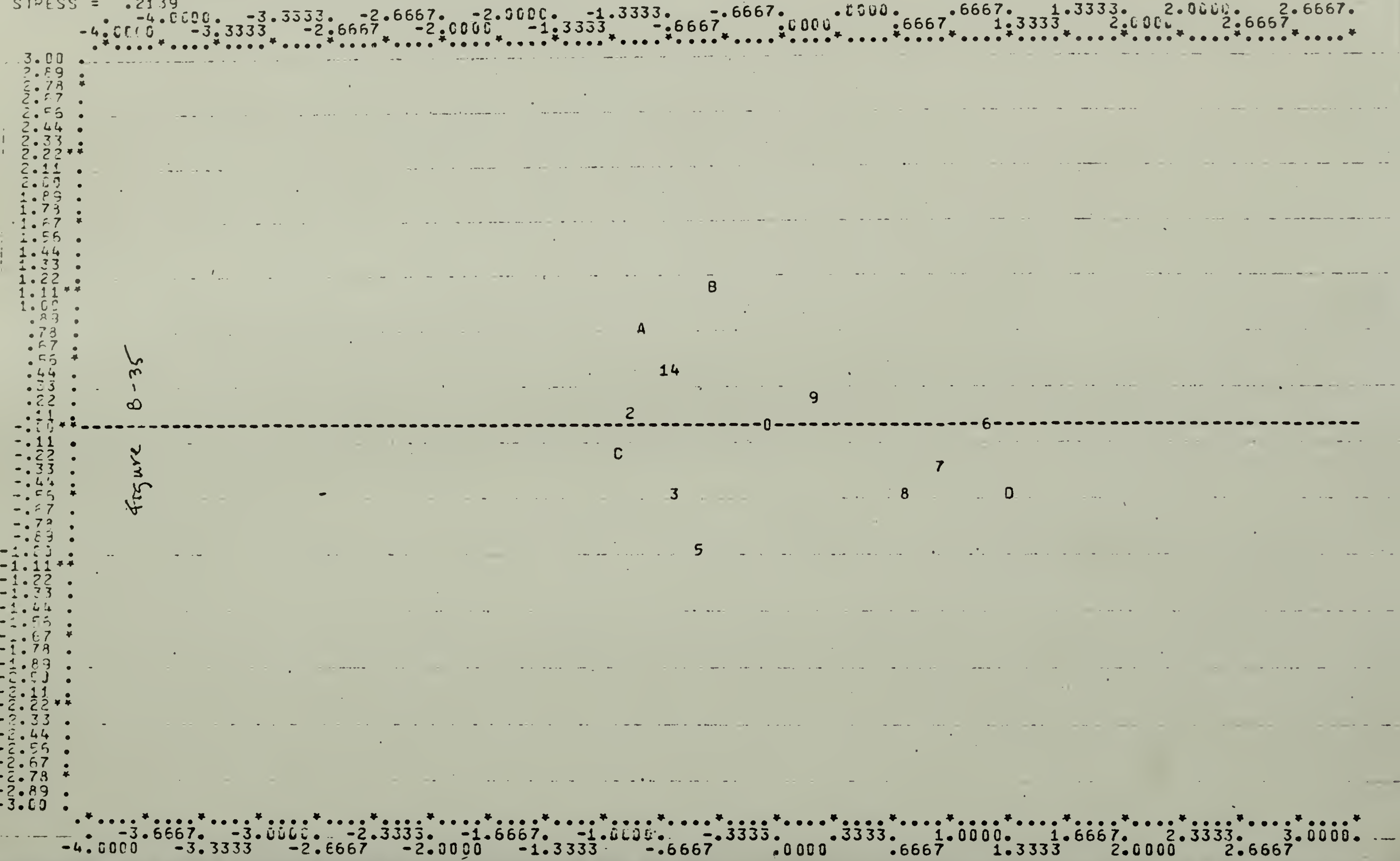


Figure B-35

TWO SPACE CONFIGURATION FOR ST DISTANCE, ST/EA(1)
STRESS = .2893

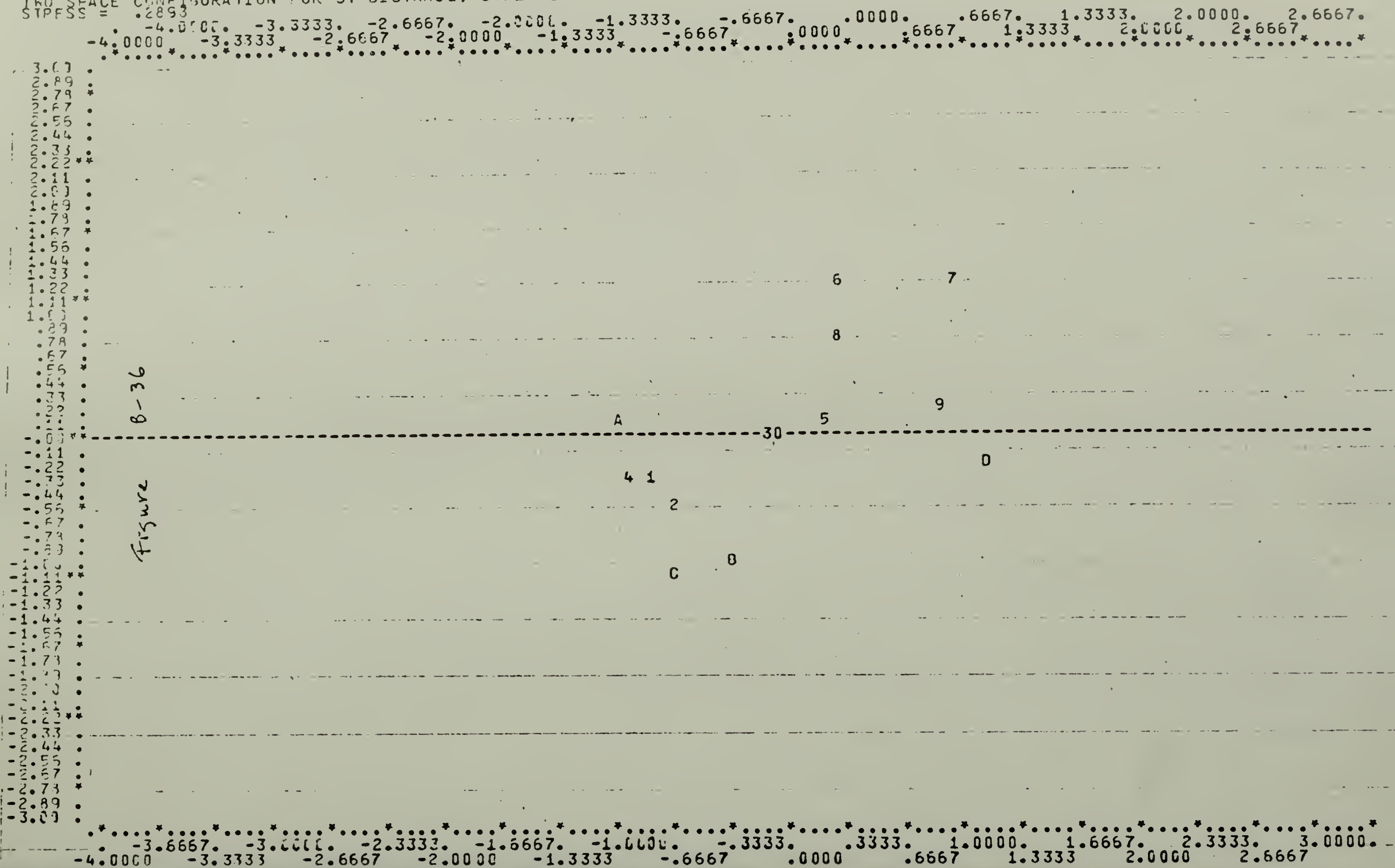
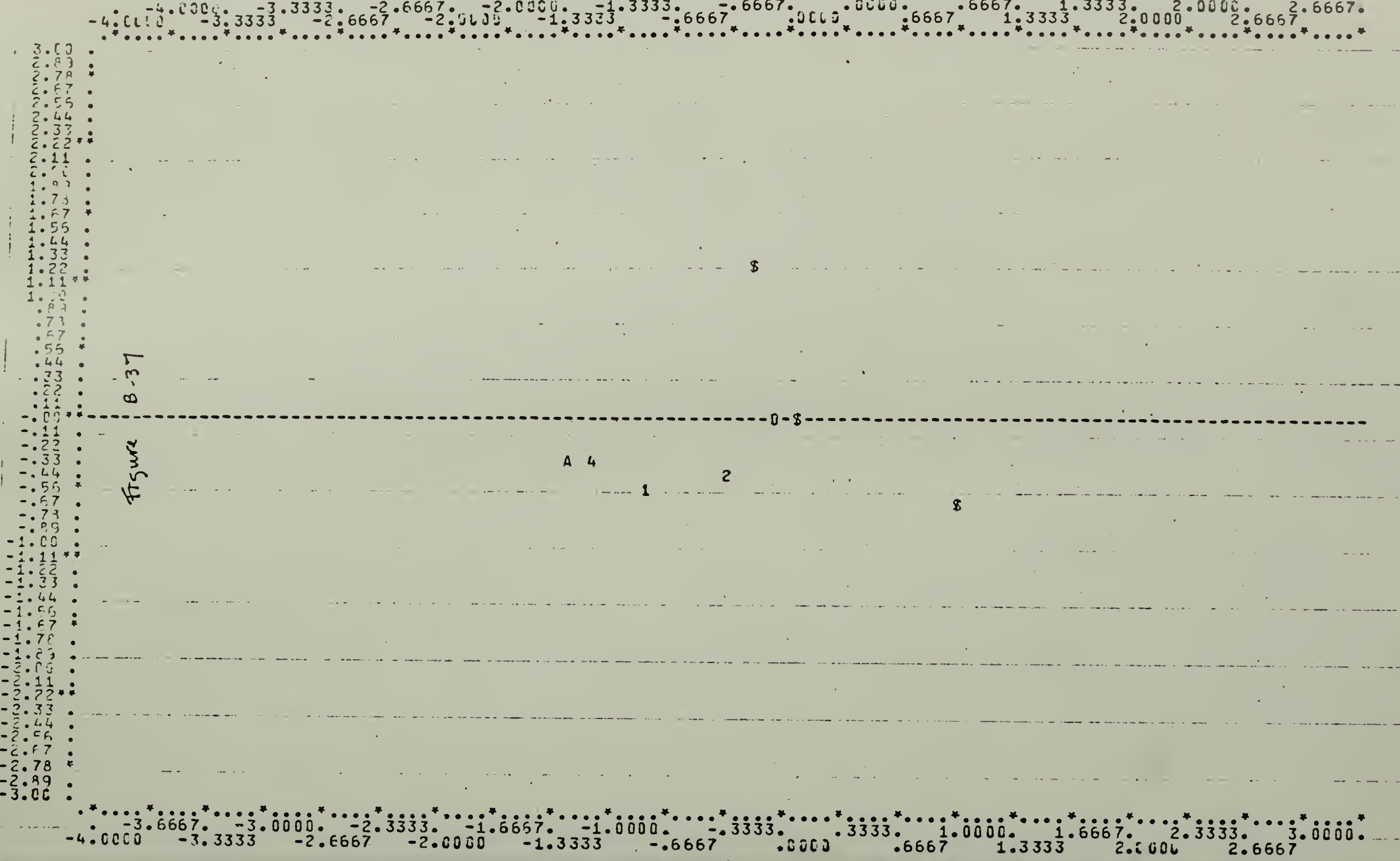


Figure B-36

TWO SPACE CONFIGURATION FOR EA RELATEDNESS, ST/EA(2)
STRESS = .5908



TWO SPACE CONFIGURATION FOR ST DISTANCE, ST/EA(2)

STRESS = .3966

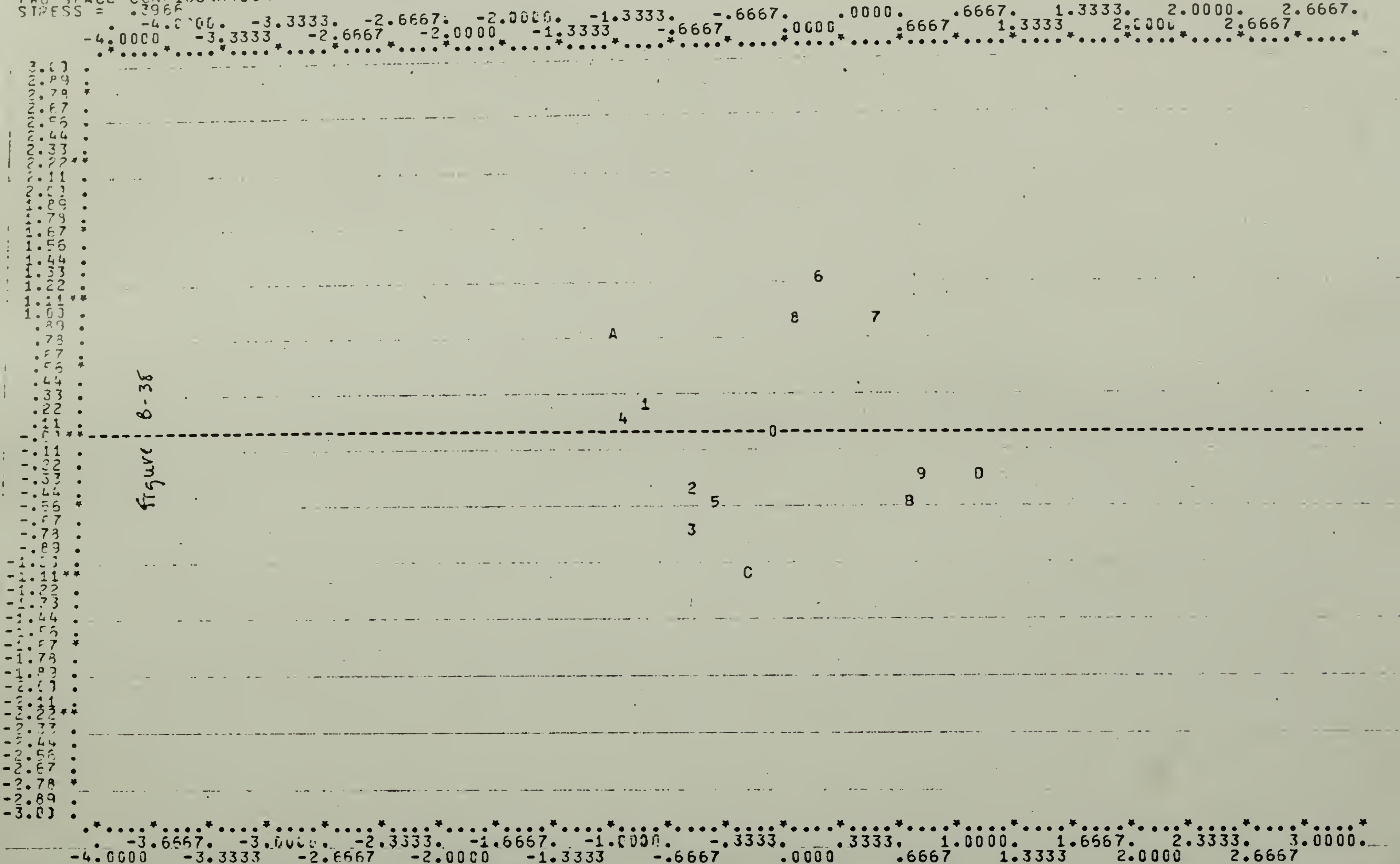
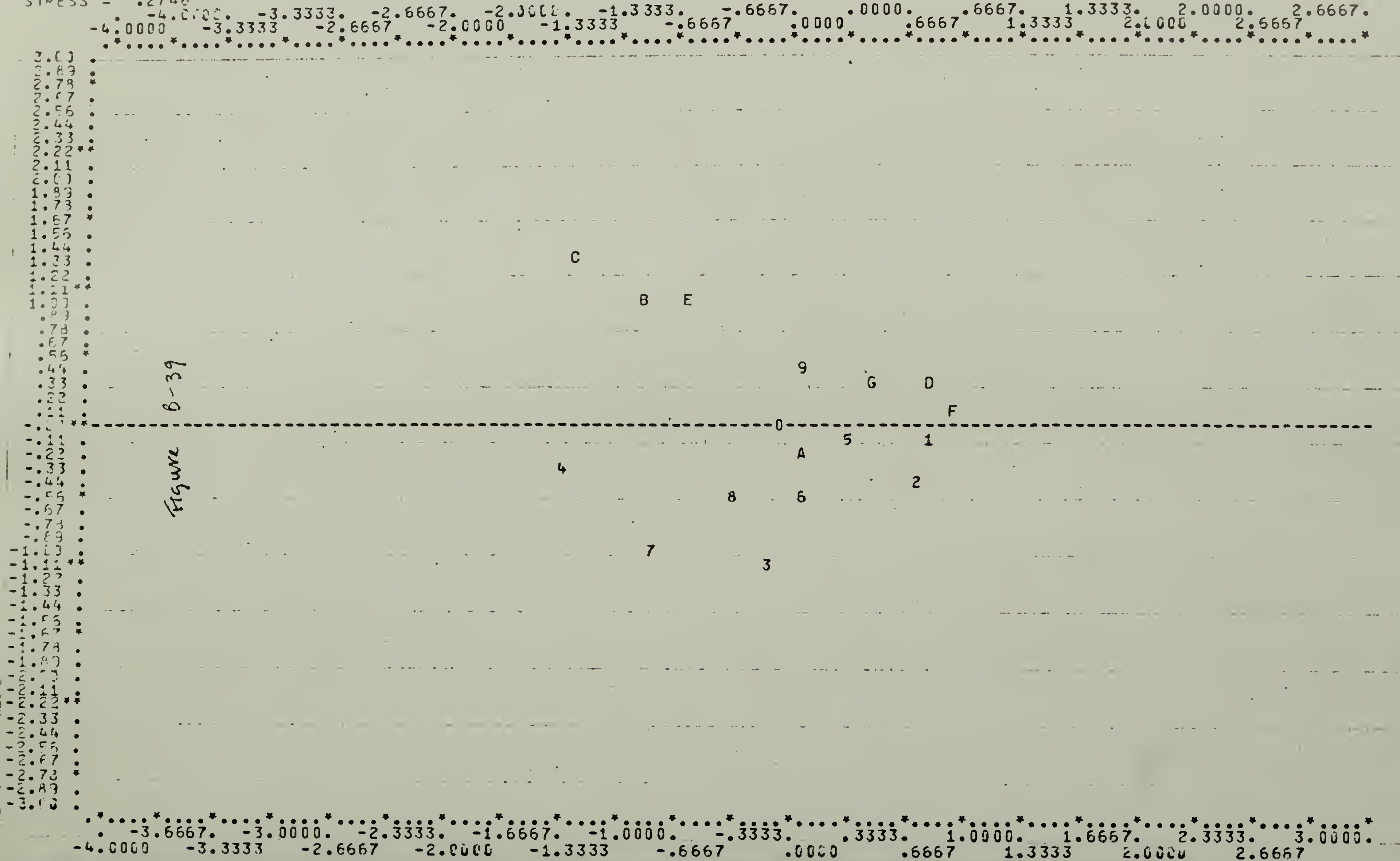


Figure B-38

TWO SPACE CONFIGURATION FOR HC RELATEDNESS, HC/EA(U)
STRESS = .2746



TWO-SPACE CONFIGURATION FOR HC DISTANCE, HC/EA(U)
STRESS = .3286

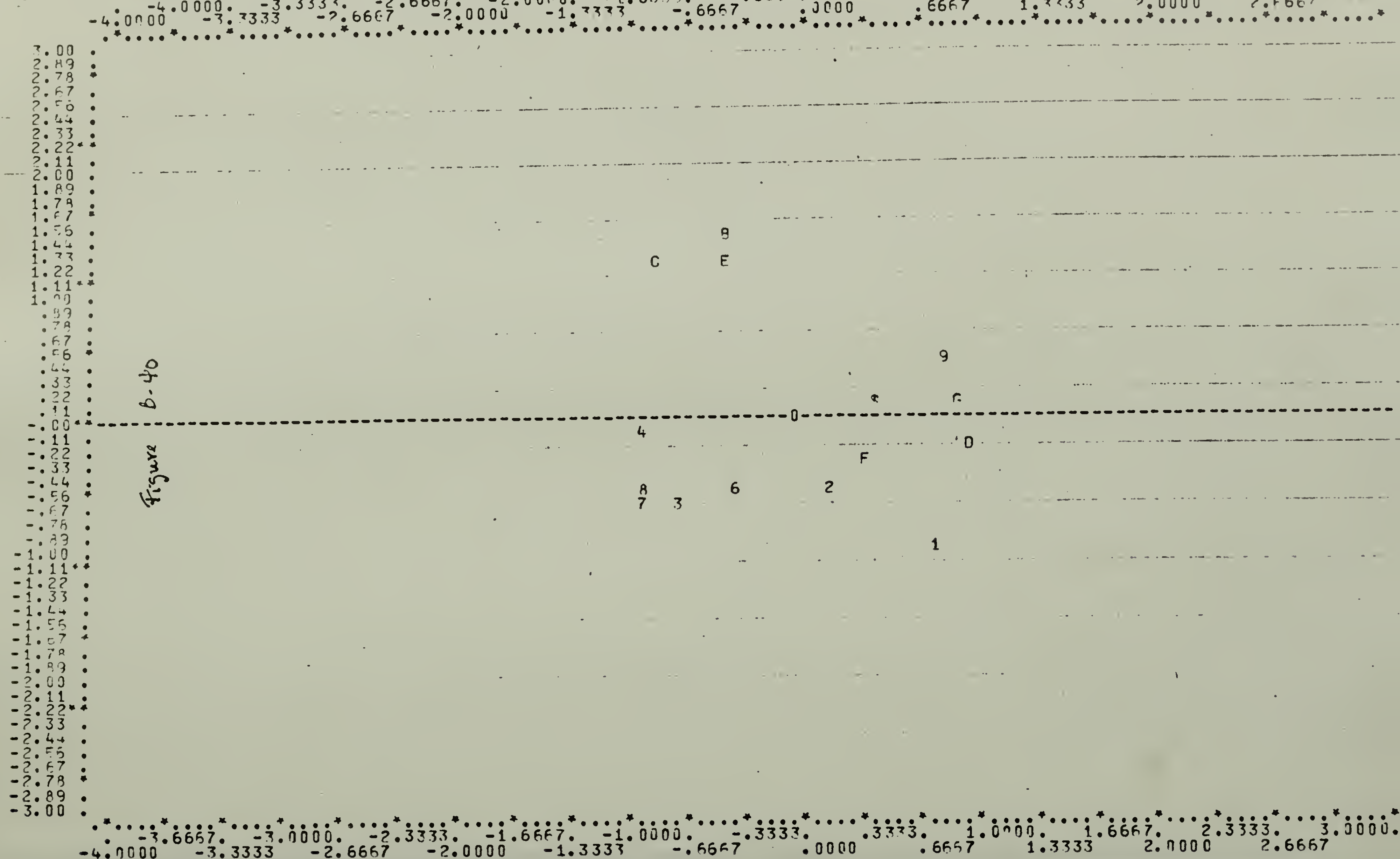
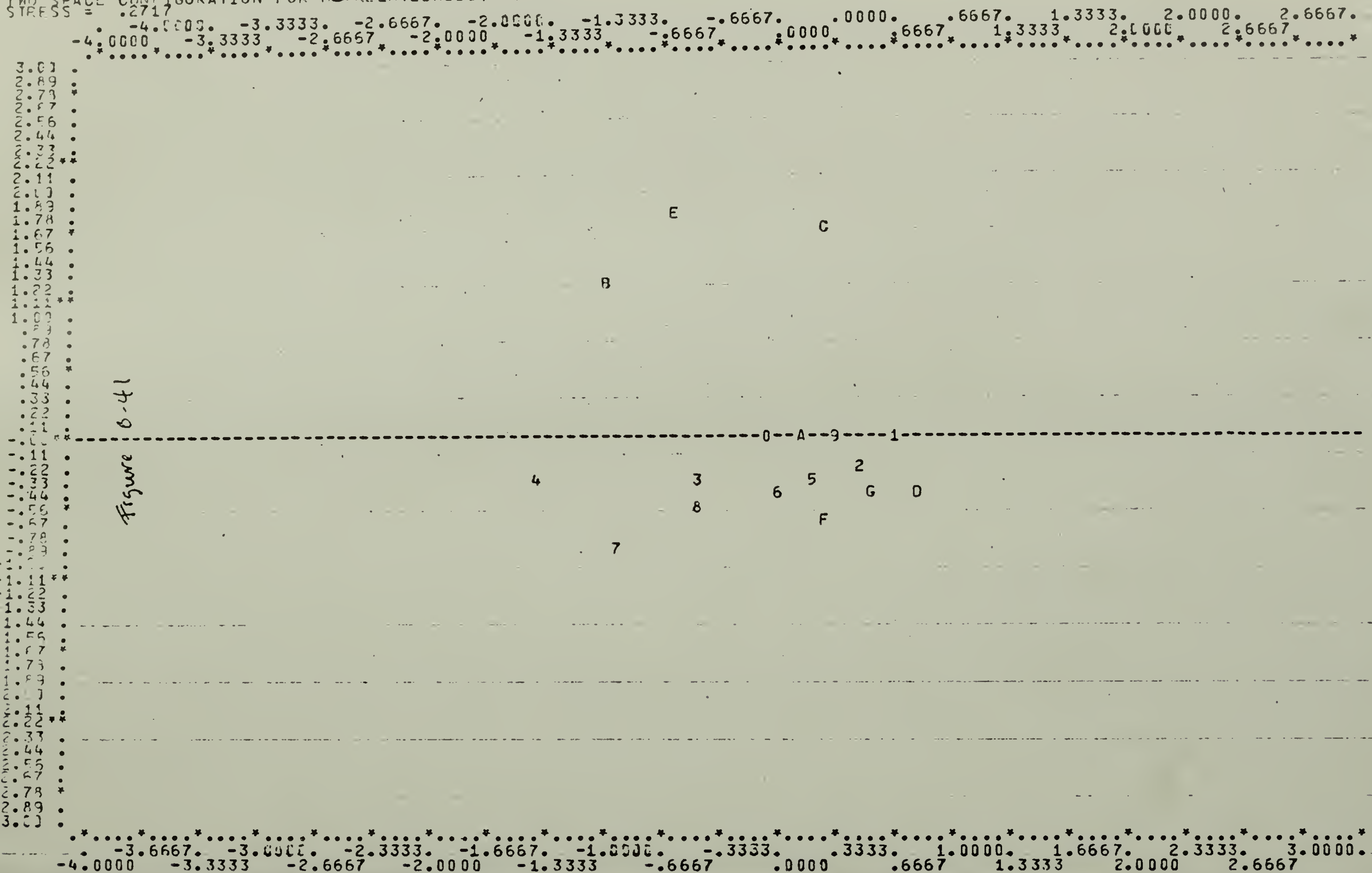


Figure B-40

TWO SPACE CONFIGURATION FOR HC RELATEDNESS, HC/EA

STRESS = .2717



TWO SPACE CONFIGURATION FOR HC DISTANCE, HC/EA
STRESS = .4094

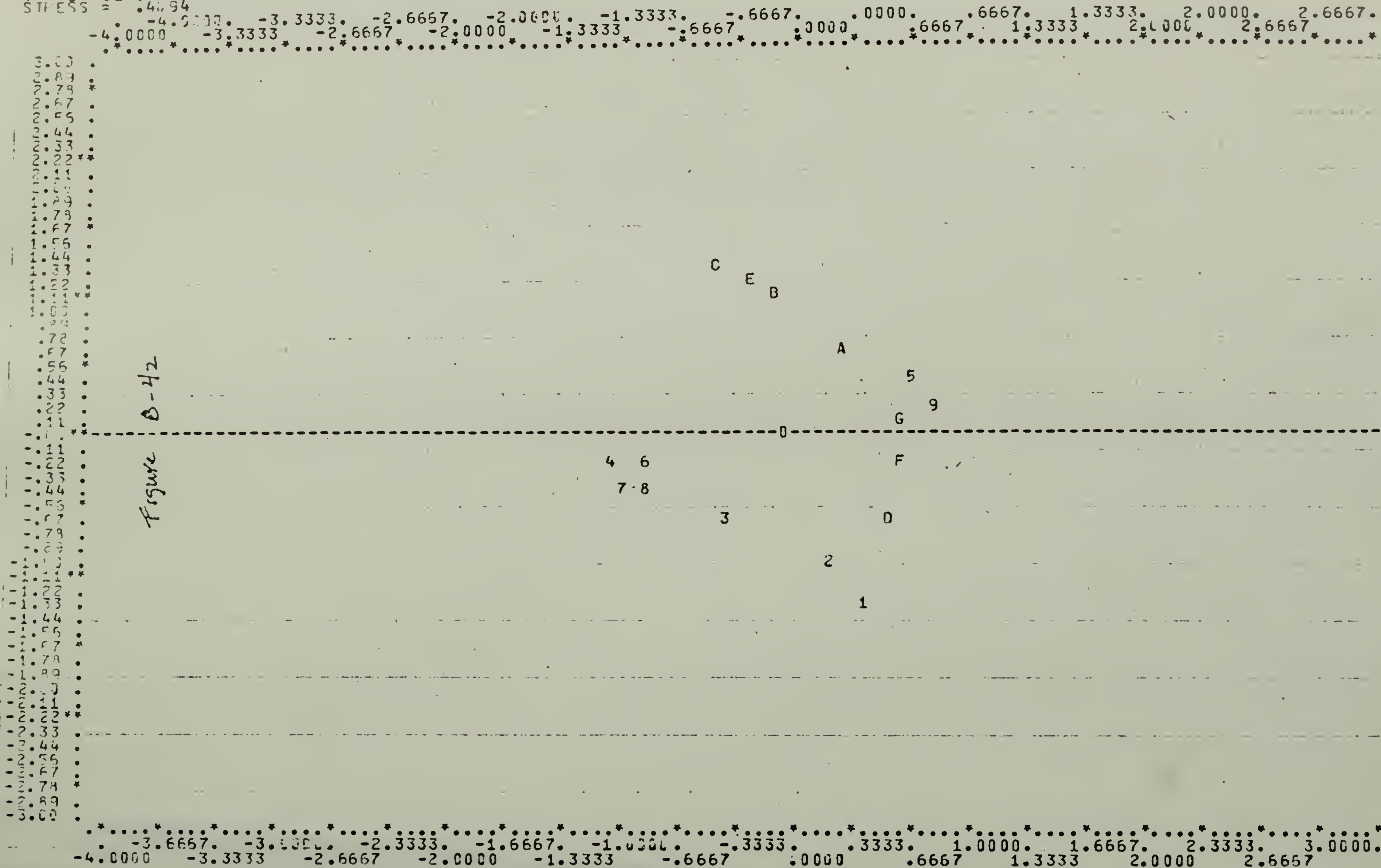


Figure B-42

TWO SPACE CONFIGURATION FOR HA RELATEDNESS, HA/EA(U)
STRESS = .3008

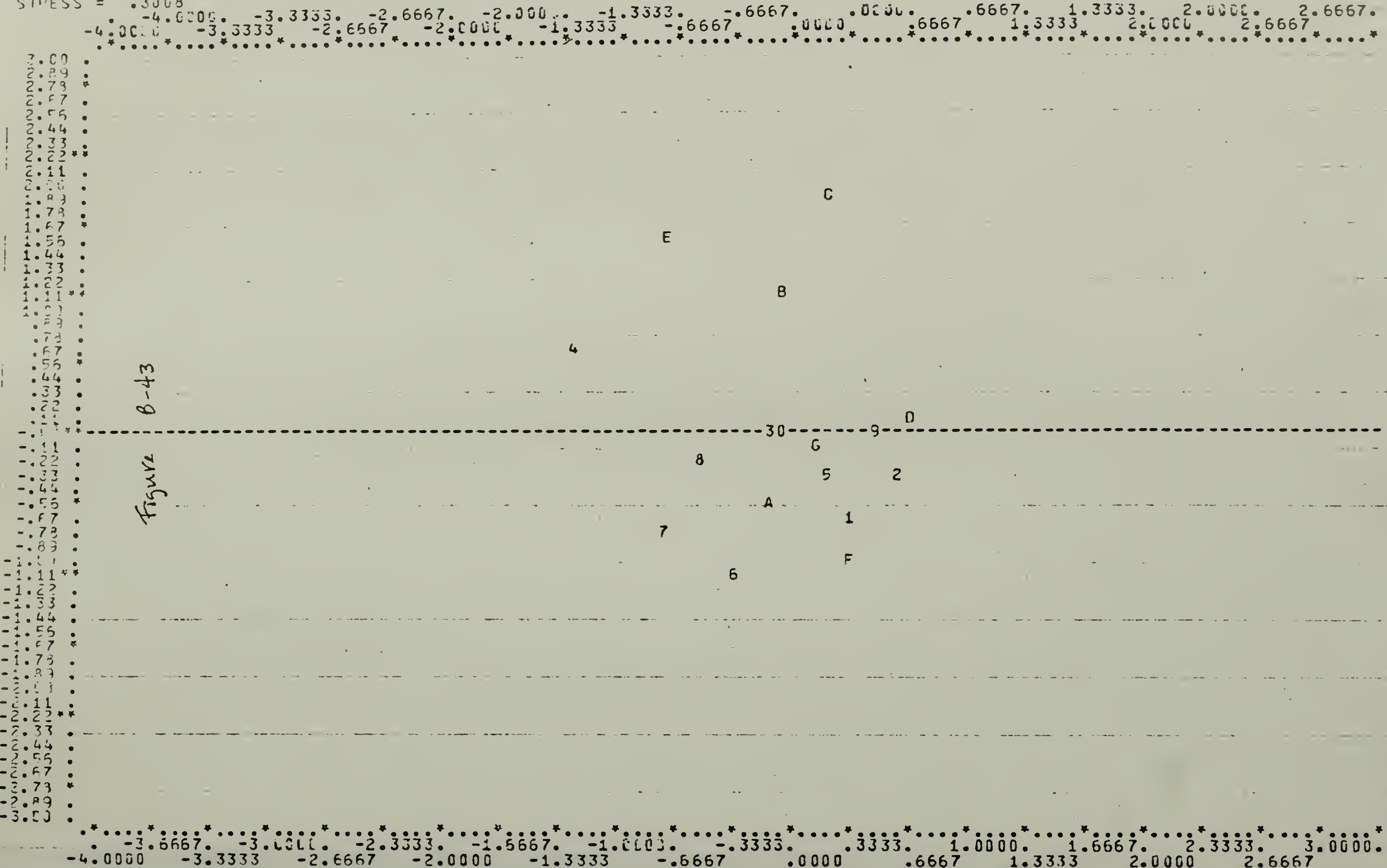


Figure B-43

TWO SPACE CONFIGURATION FOR HA DISTANCE, HA/EA(U)
STRESS = .2731

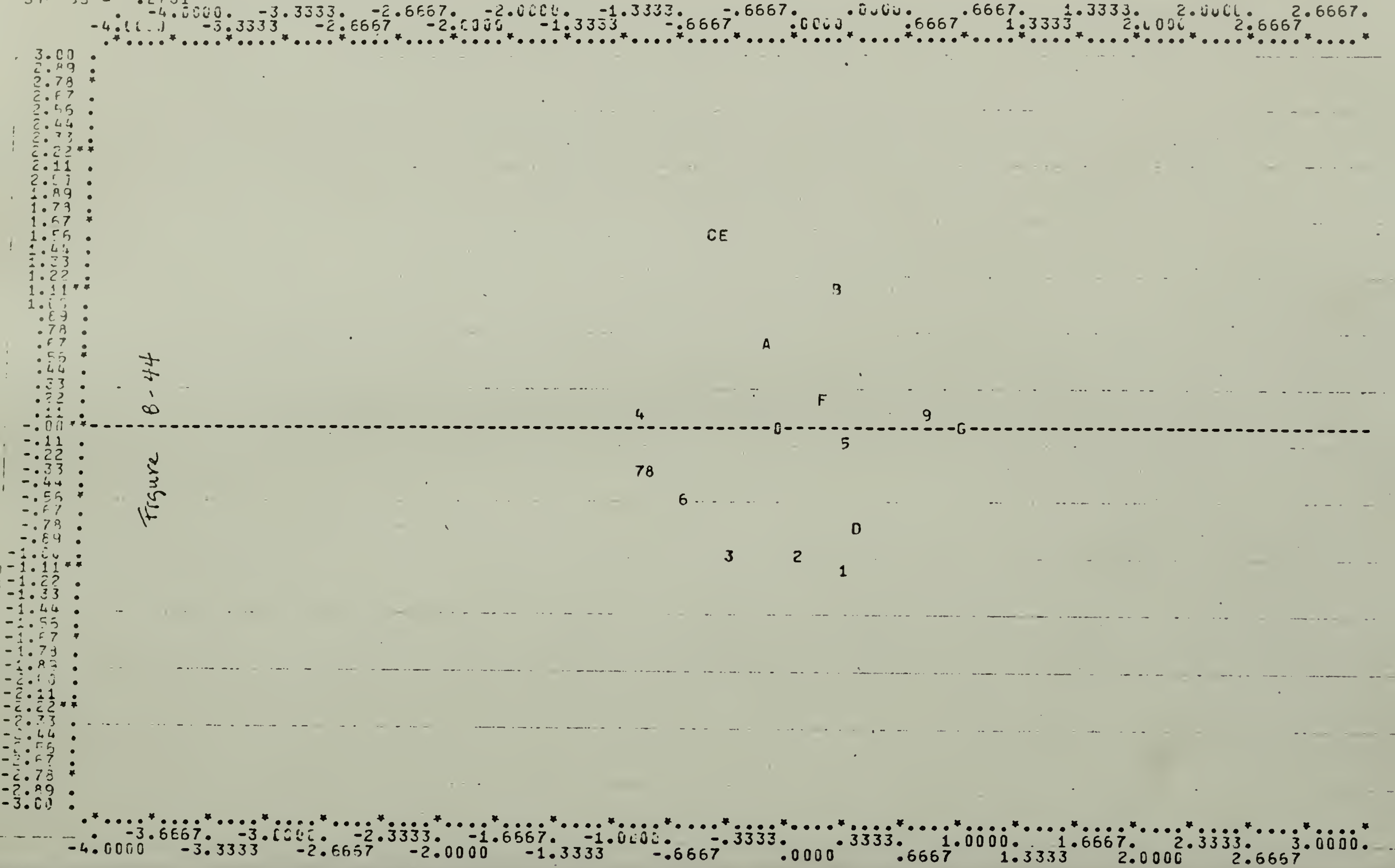
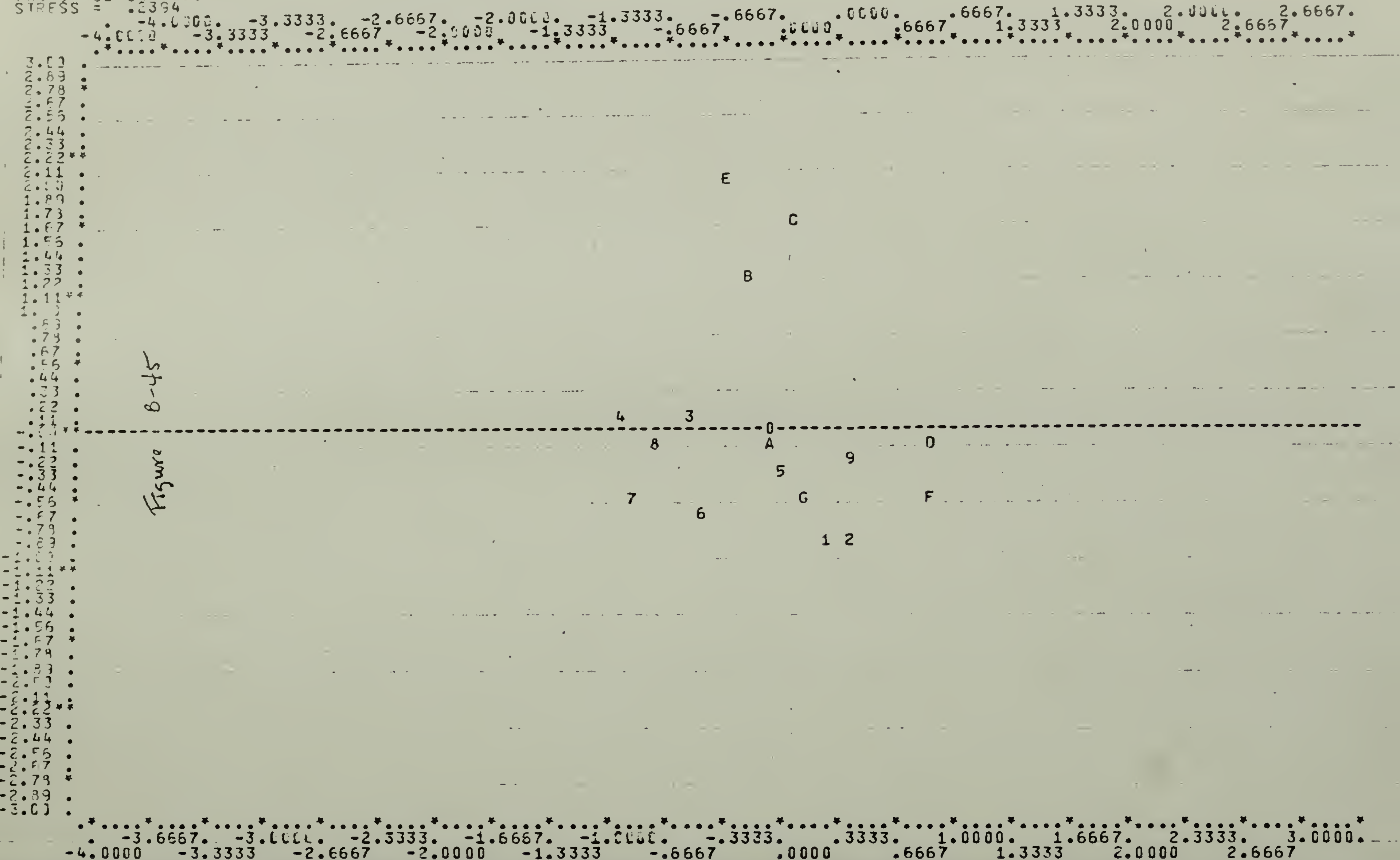


Figure B-44

TWO SPACE CONFIGURATION FOR HA RELATEDNESS, HA/EA
STRESS = .2394



THE SPACE CONFIGURATION FOR HA DISTANCE, HA/EA
STRESS = .2330

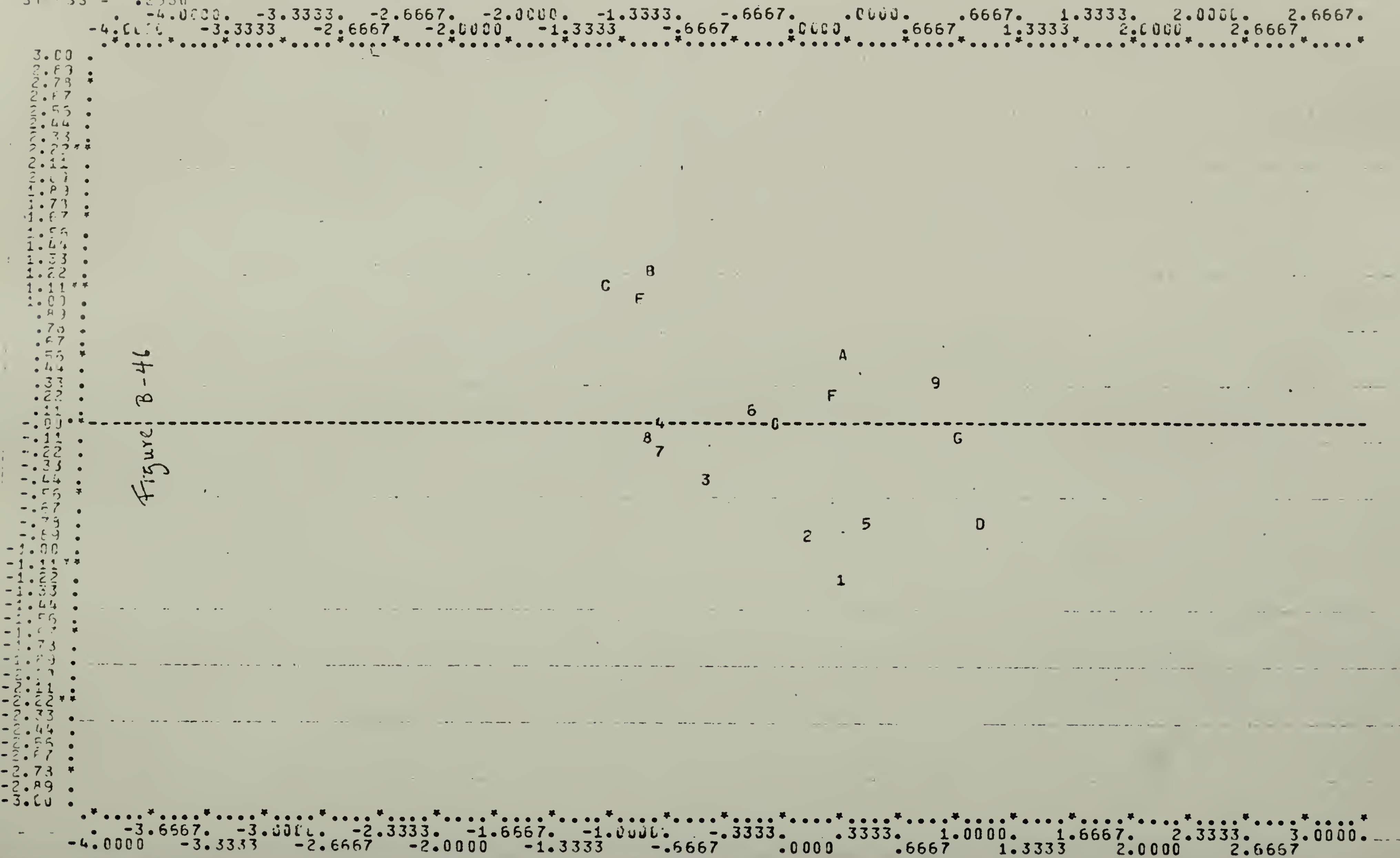


Figure B-46

APPENDIX C: Raw Data

Tables C-1 - C-3: Content Structure Matrices

Tables C-4 - C-23: Cognitive Structure Matrices

Table C-24: Number of Idea Units Recalled by Individual Subjects

TABLE C-1

Content Structure Summary Matrix, E Passage

	CD	CF	PO	ME	EL	SR	CL	AS	CO	CE	TS	MFF	AV
CD	1.0	.33	0	.50	0	0	.25	0	0	.25	.33	.25	.25
CF	0	1.0	0	0	.50	0	0	0	0	0	0	0	0
PO	0	0	1.0	.50	.50	0	0	0	0	0	0	0	0
ME	.50	0	.50	1.0	.50	.20	0	.33	0	.50	0	0	0
EL	0	.50	.50	.50	1.0	.25	0	.33	.50	0	0	.25	.20
SR	0	0	0	0	.25	1.0	.50	.50	0	0	0	0	0
CL	.25	0	0	0	0	.33	1.0	.50	0	0	.33	.33	.33
AS	.50	0	0	0	.33	.50	.50	1.0	.50	0	0	0	.17
CO	0	.50	.50	0	.50	0	0	.50	1.0	0	0	.33	.25
CE	0	0	0	.50	0	0	0	0	0	1.0	0	0	0
TS	.25	0	0	0	0	0	.33	0	0	0	1.0	.33	0
MFF	.33	.50	.33	0	.33	0	.33	0	.33	0	.33	1.0	0
AV	0	0	0	0	0	0	.33	0	0	0	0	0	1.0

TABLE C-2

Content Structure Summary Matrix, HC Passage

HF	X	33	50	0	50	0	33	0	0	50	0	0	0	0	0	0
CD	33	X	20	0	50	0	0	0	0	0	0	0	0	0	0	0
ME	50	0	X	0	0	25	33	33	20	0	33	50	33	0	20	25
SR	0	0	0	X	0	0	50	50	25	0	0	0	0	0	0	0
TM	50	0	0	0	X	0	0	0	0	0	0	0	0	0	0	0
EL	0	0	25	50	0	X	50	50	50	50	0	0	0	0	0	50
BM	0	0	33	50	0	50	X	50	0	50	0	0	0	0	0	0
CL	0	0	33	50	0	50	50	X	50	0	0	0	0	0	0	50
AV	0	0	0	25	0	50	0	50	X	0	0	0	50	0	50	0
CO	50	0	0	0	0	50	50	0	0	X	0	0	0	0	0	0
PR	33	0	50	0	0	0	0	0	0	0	X	33	0	0	0	0
IMP	33	0	50	50	0	0	0	33	25	0	33	X	0	0	33	0
TEM	0	0	0	0	0	33	0	33	50	33	0	0	X	0	50	50
DIS	0	0	0	0	0	0	50	0	0	0	0	0	0	X	0	0
TR	0	0	0	0	0	0	0	0	50	0	0	0	50	0	X	50
TA	0	0	0	0	0	50	25	50	50	33	0	0	25	0	50	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-3

Content Structure Summary Matrix, HA Passage

HF	X	33	50	0	50	0	0	0	0	0	0	0	0	0	0	0
CD	33	X	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	33	0	X	33	0	0	0	50	17	0	50	50	33	0	20	14
SR	0	0	33	X	0	0	0	50	0	0	0	0	0	0	33	0
TM	50	0	0	0	X	0	0	0	0	0	0	0	0	0	0	0
EL	0	0	0	0	0	X	33	50	50	50	0	0	0	0	0	33
BM	0	0	0	0	0	33	X	50	0	50	0	0	0	0	20	20
CL	0	0	50	50	0	50	50	X	50	50	0	0	33	50	25	50
AV	0	0	17	0	0	50	0	50	X	0	0	0	50	0	50	50
CO	33	0	0	0	0	50	50	50	0	X	0	0	0	0	0	0
PR	33	0	50	0	0	0	0	33	0	0	X	33	0	50	0	0
IMP	33	0	50	0	0	0	0	33	0	0	33	X	0	0	50	0
TEM	0	0	50	0	0	0	0	33	50	25	0	0	X	0	33	33
DIS	0	0	0	0	0	0	0	50	0	0	0	0	0	X	0	0
TR	0	0	0	0	0	0	0	0	50	0	0	0	33	0	X	0
TA	0	0	17	0	0	33	33	50	50	50	0	0	20	0	0	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-4

Cognitive Structure Summary Matrix, E Passage (WA test), HC-EA/U

CD	X												
CF	27	X											
PO	14	18	X										
ME	51	18	07	X									
EL	21	24	16	14	X								
SR	18	12	03	24	10	X							
CL	21	15	02	28	17	42	X						
AS	12	10	06	13	26	19	28	X					
CO	12	20	09	13	25	15	17	15	X				
CE	17	14	04	18	14	13	18	12	15	X			
TS	08	09	04	06	06	06	08	07	14	11	X		
MFF	11	19	34	04	14	04	05	08	12	10	07	X	
AV	08	12	03	10	13	09	13	09	28	11	20	08	X

Note: Decimals have been omitted; all numbers are two place decimals of the form, .xx.

TABLE C-5

Cognitive Structure Summary Matrix, E Passage, HC-EA/U, (GC test)

CD	X												
CF	32	X											
PO	28	35	X										
ME	43	29	28	X									
EL	28	31	29	29	X								
SR	36	28	23	33	28	X							
CL	30	23	23	33	35	34	X						
AS	32	26	23	36	37	35	39	X					
CO	25	33	28	24	40	25	28	28	X				
CE	33	37	28	31	30	36	28	26	32	X			
TS	24	27	23	23	24	26	20	27	30	34	X		
MFF	25	33	34	25	27	29	23	24	29	32	34	X	
AV	16	30	28	22	32	27	25	26	42	29	34	31	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-6

Cognitive Structure Summary Matrix, E Passage, HC-EA, (WA test)

CD	X												
CF	21	X											
PO	07	15	X										
ME	50	24	08	X									
EL	16	22	16	14	X								
SR	15	16	05	22	16	X							
CL	18	13	06	25	19	37	X						
AS	12	13	08	15	29	24	31	X					
CO	10	18	07	12	30	11	14	17	X				
CE	22	22	05	28	14	16	14	10	14	X			
TS	15	14	04	11	12	08	07	06	16	15	X		
MFF	08	19	31	11	18	09	07	17	14	10	10	X	
AV	11	17	06	14	16	08	12	10	21	14	19	09	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-7

Cognitive Structure Summary Matrix, E Passage, HC-EA, (GC test)

CD	X												
CF	31	X											
PO	25	33	X										
ME	44	26	33	X									
EL	25	30	31	30	X								
SR	27	50	25	31	33	X							
CL	33	29	25	40	41	39	X						
AS	30	26	28	36	38	38	45	X					
CO	22	33	30	22	30	26	23	27	X				
CE	32	36	26	31	27	35	30	27	26	X			
TS	21	31	30	21	23	25	21	24	34	30	X		
MFF	22	35	35	20	28	25	23	26	31	30	34	X	
AV	26	34	26	20	24	27	20	22	40	29	35	30	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-8

Cognitive Structure Summary Matrix, E Passage, HA-EA/U, (WA test)

CD	X												
CF	22	X											
PO	13	17	X										
ME	43	21	11	X									
EL	14	27	18	17	X								
SR	18	12	04	18	15	X							
CL	21	15	05	21	19	32	X						
AS	12	16	09	13	28	19	24	X					
CO	13	18	12	11	32	12	16	17	X				
CE	26	20	05	18	16	19	20	18	18	X			
TS	16	16	04	10	16	07	12	11	24	15	X		
MFF	16	15	31	10	20	07	10	10	15	16	10	X	
AV	15	15	11	14	25	14	17	16	34	17	26	12	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-9

Cognitive Structure Summary Matrix, E Passage, HA-EA/U, (GC test)

CD	X												
CF	23	X											
PO	22	30	X										
ME	45	25	24	X									
EL	24	30	28	29	X								
SR	25	23	23	32	31	X							
CL	22	22	20	29	33	47	X						
AS	28	23	24	34	40	36	35	X					
CO	18	34	25	20	35	22	20	26	X				
CE	27	37	25	30	28	33	27	29	29	X			
TS	21	32	23	26	26	25	24	28	31	36	X		
MFF	20	34	38	23	28	24	23	26	29	33	26	X	
AV	21	32	22	21	33	23	21	23	42	32	31	24	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-10

Cognitive Structure Summary Matrix, E Passage, HA-EA, (WA test)

CD	X												
CF	22	X											
PO	11	17	X										
ME	37	15	17	X									
EL	17	19	18	15	X								
SR	18	13	03	27	15	X							
CL	19	15	05	33	21	37	X						
AS	15	14	06	18	26	23	31	X					
CO	10	16	05	10	30	11	16	15	X				
CE	18	13	07	18	13	18	18	10	11	X			
TS	15	11	06	12	12	09	07	10	22	13	X		
MFF	10	13	28	06	21	03	05	14	16	08	08	X	
AV	07	13	06	10	18	06	11	08	31	12	25	08	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-11

Cognitive Structure Summary Matrix, E Passage, HA-EA, (GC test)

CD	X												
CF	35	X											
PO	24	32	X										
ME	49	29	23	X									
EL	24	31	29	26	X								
SR	29	27	21	32	27	X							
CL	26	25	23	30	35	37	X						
AS	28	26	25	36	37	38	41	X					
CO	22	29	26	22	32	26	23	26	X				
CE	36	34	25	33	25	35	33	31	27	X			
TS	26	29	23	25	27	29	21	27	36	36	X		
MFF	23	30	34	23	25	27	22	26	35	30	31	X	
AV	23	29	27	22	26	25	21	24	39	33	40	33	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-12

Cognitive Structure Summary Matrix, E Passage, ST-EA, (1st WA test)

CD	X												
CF	27	X											
PO	18	28	X										
ME	45	36	23	X									
EL	12	14	36	12	X								
SR	07	08	07	09	07	X							
CL	09	05	12	12	11	37	X						
AS	06	08	12	08	15	27	38	X					
CO	19	16	15	20	12	12	18	21	X				
CE	28	24	10	43	07	05	06	04	15	X			
TS	13	17	09	25	03	04	07	10	14	20	X		
MFF	18	23	19	23	15	07	09	10	11	14	17	X	
AV	08	05	06	05	04	21	31	19	12	02	02	06	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-13

Cognitive Structure Summary Matrix, E Passage, ST-EA, (1st GC test)

CD	X												
CF	40	X											
PO	30	33	X										
ME	42	40	30	X									
EL	26	30	45	27	X								
SR	24	25	25	22	27	X							
CL	22	20	23	21	25	39	X						
AS	28	24	29	28	33	36	39	X					
CO	24	25	30	24	33	27	30	29	X				
CE	31	31	27	34	25	27	23	27	24	X			
TS	30	36	24	30	29	21	21	23	25	31	X		
MFF	30	37	31	30	26	22	19	22	21	26	35	X	
AV	25	25	23	22	27	26	28	29	33	23	29	24	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-14

Cognitive Structure Summary Matrix, E Passage, ST-EA (2nd WA test)

CD	X												
CF	44	X											
PO	27	42	X										
ME	64	38	27	X									
EL	35	44	56	28	X								
SR	27	29	24	39	31	X							
CL	22	25	14	28	31	50	X						
AS	27	23	17	30	34	39	47	X					
CO	30	31	26	26	35	32	26	23	X				
CE	37	27	23	47	22	29	29	28	30	X			
TS	36	30	16	31	22	20	24	19	45	33	X		
MFF	27	33	48	22	48	24	17	20	30	23	16	X	
AV	27	26	18	23	24	25	30	18	41	18	41	24	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-15

Cognitive Structure Summary Matrix, E Passage, ST-EA (2nd CC test)

CD	X												
CF	39	X											
PO	32	38	X										
ME	43	37	31	X									
EL	34	45	47	35	X								
SR	30	25	26	30	29	X							
CL	31	31	29	28	28	42	X						
AS	35	27	33	31	33	44	50	X					
CO	30	30	32	28	36	26	35	29	X				
CE	34	37	27	37	27	34	23	35	22	X			
TS	31	39	27	30	30	24	24	26	37	31	X		
MFF	29	34	37	33	37	24	26	26	36	23	31	X	
AV	26	26	24	25	28	23	34	29	40	25	48	28	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-16

Cognitive Structure Summary Matrix, HC Passage, HC-EA/U, (WA test)

HF	X															
CD	25	X														
ME	08	19	X													
SR	04	04	11	X												
TM	18	20	10	07	X											
EL	13	14	15	09	22	X										
EM	06	12	14	16	11	20	X									
CL	15	14	21	20	17	29	26	X								
AV	14	11	08	08	19	19	08	13	X							
CO	15	14	12	10	27	31	15	19	23	X						
PR	05	08	07	12	09	06	04	09	11	09	X					
IMP	08	04	04	09	06	02	02	07	10	18	17	X				
TEM	18	22	10	04	16	12	05	10	25	15	08	03	X			
DIS	06	08	07	12	08	10	04	08	14	12	26	15	09	X		
TR	18	28	09	05	13	15	06	11	10	15	09	03	16	11	X	
TA	20	19	11	08	21	19	07	10	28	24	11	07	26	11	15	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-17

Cognitive Structure Summary Matrix, HC Passage, HC-EA/U, (GC test)

HF	X															
CD	39	X														
ME	30	36	X													
SR	21	29	32	X												
TM	28	35	25	30	X											
EL	24	29	31	28	29	X										
EM	23	28	34	33	25	36	X									
CL	23	30	36	33	24	37	40	X								
AV	23	23	20	23	34	29	24	26	X							
CC	25	29	24	23	41	34	29	26	35	X						
PR	20	22	24	25	23	18	18	22	24	21	X					
IMP	17	26	24	25	25	23	22	26	22	23	32	X				
THM	36	32	27	27	32	23	23	22	35	29	25	19	X			
DIS	18	23	21	25	28	22	21	25	26	26	37	37	22	X		
TR	32	37	26	27	41	32	26	23	27	31	23	24	27	25	X	
TA	29	30	22	23	36	25	22	24	48	36	20	22	36	24	30	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-18

Cognitive Structure Summary Matrix, HC Passage, HC-EA, (WA test)

HF	X															
CD	25	X														
ME	09	19	X													
SR	05	06	14	X												
TM	16	25	11	08	X											
AL	13	17	11	11	19	X										
EM	08	06	14	15	11	16	X									
CL	14	11	19	18	13	22	35	X								
AT	11	13	11	07	18	15	07	13	X							
CO	12	16	09	07	19	25	11	16	23	X						
PR	07	07	06	06	07	07	04	07	05	10	X					
IMP	07	07	09	06	06	06	04	06	06	08	06	X				
IEM	12	19	13	05	16	14	06	06	12	17	06	05	X			
DIS	04	05	06	07	05	04	04	04	08	08	14	17	04	X		
TR	15	19	14	07	17	19	09	14	16	15	05	06	14	06	X	
TA	13	25	10	05	24	20	08	12	20	18	06	07	29	04	20	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-19

Cognitive Structure Summary Matrix, HC Passage, HC-SA, (SC test)

HF	X															
CD	36	X														
ME	34	36	X													
SR	23	24	39	X												
TM	26	30	25	21	X											
EL	22	25	27	31	27	X										
SM	23	24	36	37	26	40	X									
CL	24	30	37	42	24	37	46	X								
AT	22	24	20	23	34	30	24	26	X							
CO	20	24	24	26	37	30	26	26	34	X						
PA	23	26	24	26	28	23	22	22	27	30	X					
IMP	19	22	25	27	25	20	23	23	21	31	34	X				
TEM	30	30	32	24	28	24	24	28	31	26	21	22	X			
DIS	19	20	23	29	24	20	21	24	24	30	37	37	21	X		
TR	31	34	30	21	29	26	23	24	33	32	27	20	27	33	X	
TA	24	25	29	26	33	28	26	27	38	30	26	23	34	24	33	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-20

Cognitive Structure Summary Matrix, HA Passage, HA-EA/U, (WA test)

HF	X															
CD	23	X														
ME	20	31	X													
SR	13	09	17	X												
TM	19	19	19	13	X											
EL	18	14	17	12	15	X										
EM	18	12	18	13	17	23	X									
CL	15	17	25	25	14	17	22	X								
AV	14	17	18	10	15	15	14	13	X							
CO	15	17	15	11	19	21	24	20	27	X						
PR	13	13	15	13	13	08	10	13	13	13	X					
IMP	09	10	13	13	11	04	07	12	12	12	19	X				
TEM	19	22	21	10	21	09	11	14	19	16	17	09	X			
DIS	08	10	13	15	12	07	10	13	13	13	22	13	13	X		
TR	15	24	13	10	14	14	16	19	13	19	10	08	17	08	X	
TA	18	22	24	13	19	17	14	21	21	23	15	13	23	12	16	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-21

Cognitive Structure Summary Matrix, HA Passage, HA-EA/T, (CC test)

HF	X															
CD	38	X														
ME	33	39	X													
SR	24	27	30	X												
TM	27	28	29	24	X											
EL	23	28	32	27	29	X										
SM	21	25	29	32	26	39	X									
CL	27	24	35	34	25	33	38	X								
AV	23	25	22	22	37	23	21	20	X							
CO	20	21	22	25	29	32	30	25	29	X						
PA	20	18	21	27	24	22	21	22	27	27	X					
IMP	17	17	19	24	20	19	18	22	19	30	28	X				
TEM	34	32	32	24	30	27	25	24	32	23	22	20	X			
DIS	16	17	16	27	23	20	21	23	21	29	36	44	15	X		
TR	26	29	22	26	33	26	28	30	33	32	27	28	30	[illegible]	X	
TA	26	24	22	23	28	24	23	20	35	26	28	19	30	[illegible]	32	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-22

Cognitive Structure Summary Matrix, HA Passage, HA-EA, (WA test)

HF	X															
CD	46	X														
ME	22	31	X													
SR	19	16	32	X												
TM	28	27	23	23	X											
EL	24	19	22	30	31	X										
EM	21	19	24	29	23	37	X									
CL	22	22	40	45	27	39	45	X								
AV	24	26	20	21	33	27	21	25	X							
CO	29	24	25	27	34	44	37	32	31	X						
PR	16	16	18	22	19	17	18	21	19	23	X					
IMP	13	16	21	15	14	12	13	16	13	19	26	X				
TEM	31	22	22	17	31	19	13	14	32	26	19	14	X			
DIS	10	09	17	17	12	10	12	15	13	14	44	37	11	X		
TR	22	27	19	14	27	21	17	17	32	28	16	11	23	11	X	
TA	32	31	19	19	37	32	23	22	36	37	17	16	31	12	23	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-23

Cognitive Structure Summary Matrix, HA Passage, HA-EA, (GC test)

HF	X															
CD	44	X														
ME	35	39	X													
SR	23	25	39	X												
TM	35	33	29	25	X											
EL	24	24	32	34	30	X										
SM	23	24	37	36	23	39	X									
CL	23	25	42	43	23	38	42	X								
AV	22	25	21	23	27	31	24	23	X							
CO	21	25	24	24	26	38	31	25	41	X						
PR	18	22	26	26	20	24	23	25	23	25	X					
IMP	18	22	27	28	21	24	22	24	21	25	35	X				
TEM	33	30	27	22	29	22	20	21	29	22	20	19	X			
DIS	17	22	27	29	21	27	27	26	22	27	46	45	21	X		
TR	25	29	29	27	30	30	26	23	27	35	24	24	27	23	X	
TA	27	26	22	25	28	31	23	23	36	34	20	19	33	22	26	X

Note: Decimals have been omitted; all numbers are two place decimals less than one.

TABLE C-24

Number of Idea Units Recalled by Individual Subjects

GROUP: TREATMENT:	(1) HC-EA/U	(2) HC-EA	(3) HA-EA/U	(4) HA-EA	(5) ST-EA
	9	7	6	5	6
	3	11	3	4	8
	9	8	6	6	7
	4	6	3	3	8
	7	17	5	9	5
	9	11	8	9	5
	14	6	5	10	4
	9	6	6	4	8
	11	7	4	13	15
	8	11	10	4	7
	17	7	2	7	6
	14	6	4	12	6
	17	8	9	13	6
	9	15	11	7	6
	13	14	13	8	11
	10	11	5	7	12
	9	11	7	11	5
	9	7	7	15*	8
	10	9	4	16+	11
	9	6	4	12	4
	(n=20)	(n=20)	(n=20)	(n=20)	6
					(n=21)

*This student admitted to being a chemistry major with a strong background in physics.

+This student had a degree in biochemistry and also had a strong physics background.