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Normore, Lorraine Dombrowski

STRATEGIES IN SEARCHING HIERARCHICAL DATA STRUCTURES

The Ohio State University

Ph.D. 1986

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VITA

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Theses and Publications

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INTRODUCTION

Structural orderings of many different kinds—tables, hierarchies, networks, lists—are widely used as devices to aid people in using information. Even books are divided into chapters and subchapters to provide structure.

Structural orderings are particularly important in the fields of library and information science. E.C. Richardson (1930), a noted figure in the history of classification theory, said of the nature of classification:

"...the putting together of like things...
It represents also the real order of arrangement of things in the universe—a series of groups and groups of groups arranged according to the degree of likeness from the simplest to the most complex." (p. 1)

Richardson also voices a view often held by important early classification theorists like Bliss and Dewey who tried to order books to simulate the way in which the human mind orders knowledge and to reflect the structure of the world.

"As a race and as an individual, man gets his ideas helter-skelter. When he starts to think, they are a disorderly mass, a chaos of ideas which he must reduce order by classification. The final goal of his effort is exact ideas of everything that is, arranged to the real order of things in the universe..." (p. 2)

One form of organization often chosen has been the hierarchy—the best-known example of this being the Dewey Decimal Classification System. A hierarchy is defined as a specialized form of network
structure. A network is an organization of nodes and their interconnections. In a hierarchy, the most general category is defined as the point of origin or root of the structure and subsequent categorizations represent progressively smaller subsets of the root. Each subset or node is connected to one superordinate node representing its logical parent or superset. There is a good deal of evidence, which will be described in the literature review section, that people are influenced by structural orderings, and in particular, by hierarchical orderings. The research which is to be described will investigate some characteristics of hierarchies that are relevant to behavior in situations requiring visual search and memory retrieval.

Because an increasing number of people have become the direct users of online computer information systems, factors that affect such searches are of increasing interest for applied reasons. Menu systems and organized information structures are frequently hierarchically structured, hence understanding search strategies is an important tool for designing software systems.
LITERATURE REVIEW

The purpose of the literature review is to establish the important role that hierarchies play in the organization and use of information. First, models of memory and search which consider the existence and effects of conceptual hierarchies are discussed. Second, a number of different areas which demonstrate people's awareness of the structure of information and the role this structure plays on their ability to use structural relationships are reviewed. This includes a review of work done on the use of hierarchical menu systems. Taken together this literature illustrates the role played by hierarchies in the study of human information processing.

Hierarchies as Models for Structure and Search

Two broad aspects of memory which can be investigated are structure and process. In the study of human memory, the investigation of structure and the process called search and retrieval are intimately related, for we cannot understand the way memory is searched if we know nothing of its structure nor can we draw inferences about structure from the retrieval of information from memory if we know nothing of search. For the most part, experimental studies of memory have been concerned with questions related to the structure of memory— from the nature of associations to the characteristics of memory stores and the form in which information is represented.
Search processes in memory have seldom been dealt with in an independent way. One structural concept, the hierarchy, is often used as the implicit (and sometimes explicit) form in which information is stored or which guides search. Search has been explicitly dealt with, however, by models for problem solving from the perspective of artificial intelligence.

Organization in Memory

In the study of human learning and memory, two kinds of structure have been suggested very frequently as models for conceptual structure in memory. Memory has been described as organized into a hierarchically ordered, categorically determined, embedded structure or as a more loosely connected system of associative links, some of which might be categorically determined but which might reflect any other sort of association among items, i.e., as a network. Although this literature review will deal only with conceptual memory, hierarchical organization also underlies other forms of knowledge representation. This can be seen in the analysis of case relations presented by Frederiksen (1975), of schematic organization by Jean Mandler (1978), and of story memory by Thorndyke (1975).

One of the earliest experimental measures of organization in recall was developed by Bousfield (1953). Using lists consisting of 60 randomly ordered nouns taken from four different categories, Bousfield found that subjects tended to group members of common categories together in recall to an extent far exceeding that predicted by chance. Bousfield concentrated on the role of
relatedness among words which were bound by a pattern of superordinate-subordinate, i.e., hierarchical, relationships (cf. Bousfield & Cohen, 1953). The importance of these types of relationships is illustrated in Segal's (1969) finding that, given category names and members in randomly ordered to-be-learned lists, subjects tend to recall first the category name and then its members.

Several of Bousfield's contemporaries focused their attention on non-categorical associative clustering. Jenkins and his associates (e.g., Jenkins, Mink & Russell, 1958) demonstrated that clustering in recall did occur on the basis of associative links that were not purely categorical and that associative clustering was proportional to the strength of inter-item associations established by free association norms. Deese (1959) also showed that the recall of lists was affected by inter-item associative strength and suggested that the superordinate was not a key factor in the facilitatory effects of organization on recall.

The independent contributions of categorical and associative relationships were later assessed by Marshall (1967). Using lists whose members could be related either categorically or associatively and not categorically, he showed that categorical and non-categorical associative relationships exerted independent, facilitative effects upon recall by demonstrating that category membership influences organization in free recall "above and beyond the effects of association" (p. 372) and that categorical and non-categorical relationships exercise separable effects on
clustering. Since hierarchies are a straightforward way to represent the superset-subset relationships embodied in categorical classification, the evidence provided by Marshall (1967) and other is consistent with the existence of hierarchical structures in memory.

Artificial Intelligence Models of Search

Search problems are explored in the field of artificial intelligence. Winston (1984) has pointed out that search problems are present in those "situations in which one choice leads to another" (p. 87) and are "ubiquitous, popping up everywhere Artificial Intelligence researchers and student go" (p. 87).

When this type of analysis is performed on problem solving situations, the following set of definitions is often used. By convention, states (conditions, event descriptions) are depicted as nodes in a network or tree. The basic problem is to find a path (which may be just any path or often an optimal path) from some start state to some goal state. Since the type of data structure studied in this research is often the hierarchy or tree, search strategies for this data structure are defined. In a situation in which any path is as good as any other, Winston (1984) suggests that any alternative at the initial level chosen be picked and that the search works down the tree from that point "as long as there is hope of reaching the destination using the original choice" (p. 91). This is called a depth-first search. This strategy is recommended when the number of "blind alleys" do not get too deep but can be
dangerous when some node opens up a vast subtree which does not include the target node. An alternative approach which like the depth-first strategy does not depend on knowledge of the value of the to-be-searched nodes, is breadth-first search. Breadth-first searching proceeds by pushing uniformly into the search tree. The strategy looks for the target among all the nodes at a given level and then moves to the children of those nodes if the target is not found. This method will work even when the hierarchy searched is infinitely deep and is good when the number of alternatives at the choice points is not large. However, it is not efficient when the target nodes tend to be at roughly the same depth.

A number of other search strategies follow from the two basic approaches. These strategies (e.g., hill climbing, beam search, best-first search) attempt to guide search by using information about the relative goodness of the nodes as indicators of possible search paths. Because of this they depend on known or hypothesized values either for the nodes which permit the search to order the choices and to explore the most promising paths first. Other classes of search strategies are concerned with finding the best path. These strategies attempt to find optimal paths without evaluating all possible paths first. This is done by using estimates from partial paths, by adding guesses about distances remaining, and by discarding redundant paths. Other types of search strategies are concerned with adversary situations. Game programs use specialized strategies (e.g., minimax, ALPHA-BETA pruning) to estimate the likelihood that a target will be found by moving
through trees and by pruning branches which do not look like good solution paths. We will not discuss the differentiating features of these optimizing models in any detail since the structure of the task to be used in this research does not give subjects the kinds of information appropriate to determining best or optimal paths.

Computer models which represent learning and problem solving behavior as paths through a tree of possible solutions have a long history in the cognitive science literature. Newell, Shaw and Simon (1958) pointed out that the basic model for chess was as a finite, branching tree with the nodes representing positions and the branches alternative moves from each position. Playing chess consisted of evaluating alternative paths and then choosing some path based on the outcome of the evaluation. This focused interest on the study of the evaluation methods used. Samuel (1959) used a similar model for a checker playing program. Rather than evaluating strategies, Samuel investigated the adequacy with which different learning models (rote learning vs. learning by generalization) produced acceptable checker playing behavior. Tree structures are also used as a model in the early model of human symbolic learning called EPAM (Elementary Perceiver and Memorizer). Feigenbaum (1961) used what he termed discrimination nets to represent the structure of discrimination learning at some specified point in time. The terminal nodes represent stored symbolic information (image lists) and the nonterminal nodes are stored programs called tests which examine input and determine the pattern of branching through the
tree. Retrieval is represented by repeated test and branching until the name of the target image list is found.

Thus the use of hierarchies both as a model for the structure of information and as a guide for search strategies is an intrinsic part of at least one approach to the study of artificial intelligence and cognitive science.

Models for Conceptual Memory

One very influential theory of conceptual memory used the hierarchy as a structural model and as a model for search. Collins and Quillian (1969) described a model for the structure of memory which was almost purely hierarchical. This model described memory as a set of nodes with pointers to superordinate and subordinate items. In the model, attribute information was thought to be stored as a property of the most general possible node in the structure to which it might apply and not to be stored as a property of each of the possible subordinate nodes.

The model was tested by studying subjects' response time in judging the truth or falsity of a number of declarative sentences about items in the hierarchy, "a canary has wings", for example. According to the model, the searcher begins at the node representing the subject in the sentence. He may scan information at this node for properties of the concept represented by that node. If the information is unavailable at that node he will search a superordinate node for the information needed to make a decision.
about the truth or falsity of the test sentence. This is needed since Collins and Quillian (1969) state that information general to the subordinate categories is stored with the superordinate.

The examples of stimulus sentences provided in their Table 1 suggest that the searcher accesses a node from another nested under the same superordinate directly but that nodes nested under different superordinates must be accessed through common superordinate nodes. Let us work out one of their examples. There is a tree such that the tested superordinate category is "non-alcoholic beverages". "Bitter lemon", "orangeade", and "pepsi-cola" are all subcategories of this superordinate. Since they are all members of this common subordinate, true and false sentences about them are equivalently difficult. As a result, "Bitter lemon is orangeade" is the false sentence of an equivalent level of difficulty with the true sentence "Pepsi-cola is pepsi-cola". Since the implied superordinate is "non-alcoholic beverages", "wine" is resident under a different superordinate from the preceding category exemplars. Therefore "Club soda is wine" is said to require a further level of search.

The searcher is forced to work his/her way along the branching structure of the tree. To derive information about two concepts he must work from one of the concepts to a common node and then progress down an appropriate branch to the second concept. Since moving through the hierarchy is assumed to take time, the linear increase in reaction time with distance in the hierarchy separating items observed in the studies reported by Collins and Quillian (1969) is taken as evidence supporting both the cognitive structure
and the implied search strategy. (This linear trend, however, was found reliably only for 'true' sentences, suggesting that this model may be an overly simplistic description of structure and process).

A model similar in structure but conceiving of memory as less rigorously hierarchically structured was given in Collins and Loftus (1975). The information structures are not antagonistic—Collins and Loftus clearly say that their model is an extension of the Quillian model. Their model simply contains structures that are not purely hierarchical.

The search procedures implied in the two articles are, however, different. In Collins and Quillian's model, search is determined by the branch structure of the hierarchy. This is seen in their suggestion that all items of a branch at an equivalent depth are accessed equally rapidly but that items at a higher level take longer to access because the searcher must move to connecting superordinate nodes. This type of search is most closely approximated by a depth-first model for search. Depth-first models posit that search moves first down a branch and then ascends to a predefined common node and down another branch. Collins and Loftus "spreading activation" model is different. It assumes that all nodes at a given distance from the starting node are activated and that nodes which are subordinate to these first level nodes are activated as a function of their distance from the originally activated node. This does not imply a search down a single branch before proceeding to another branch but rather search dominated by common distance from the origin. This more closely approximates a
breadth-first approach to search since it posits equivalent weight for all items of a common distance. Depth-first vs. breadth-first properties help distinguish the search models evaluated in the research reported in this paper.

Models of memory, data on recall, and data from sentence verification have suggested that information is either stored in memory in a structured manner and/or that retrieval proceeds in a structured manner. In both cases, hierarchical structures are plausible candidates for the way in which memory is organized or in which retrieval or problem solving is structured.

Using Structural Information

The structure embodied in a set of information has been shown to affect people's behavior when dealing with that information. Four contexts in which such effects have been demonstrated are: in the ability of subjects to use and to generate structural orderings, in the relationship between structure and recall, in the discovery and use of structural information in the learning of serial patterns, and in the use of hierarchically organized computer menus.

Structural Orderings

Durding, Becker and Gould (1977) have demonstrated that people are able to organize sets of words according to the semantic relations inherent in the word sets. Subjects were given word sets representing the following four organizational structures: hierarchy, network, list, and table. They were told to re-write
columns of words in "such a way that the relationships they found would be obvious to someone else". They were able to arrange the lists into formats consistent with those pre-defined by the experimenters. This tendency was greatest for the word sets representing hierarchical relationships and least for the sets organized as tables. Providing 'skeleton' forms greatly increased the subjects' tendencies to organize the word sets appropriately. Forcing the subject to place the words into inappropriate organizational forms resulted in an increase in the time necessary to complete the task. Since completion time has been shown to be influenced by task difficulty, we could infer that forcing subjects to mis-use structural information results in an increase in task difficulty. People use the semantic structure inherent in a set of words as a guide to remembering.

**Effect of Structure on Recall**

Subjects are able to use explicitly defined information structures as an aid to recall. In a set of experiments now regarded as a classic, Bower, Clark, Lesgold and Winzenz (1969) demonstrated that arranging category lists in a hierarchy substantially increased the recall of items so arranged over recall of the same material randomly arranged. This effect held for both conceptual and associative hierarchies. Broadbent, Cooper and Broadbent (1978) demonstrated that both hierarchical and matrix arrangements produce better recall performance than does a randomly ordered list. Moreover, they demonstrated little difference in the effectiveness
of the two structures, suggesting that the advantages demonstrated for hierarchical arrangement in earlier studies accrue to other organizational structures as well.

Special benefits have, however, been shown to accrue to the adoption of hierarchical memory aid systems. Ericsson and Chase (1982; Chase and Ericsson, 1981) studied the skilled performance of a subject named SF on a digit span task. SF developed a technique for coding digits into units meaningful to himself. He grouped each digit sequence in a specific way and then arranged the groups hierarchically. He then regrouped these groups into "super groups" and these into yet higher level groups, allowing his digit span to increase to a highest digit memory scan of 82 digits. Chase and Ericsson succeeded in analyzing SF's technique well enough to be able to teach the method to another subject and transfer much of the benefit. Hierarchical structuring was an inherent part of the method's success.

Structure in Serial Patterns

In the learning of serial patterns, subjects respond to structural elements inherent in such patterns. Reber (1969) demonstrated the role of rule structure in serial pattern learning. Reber's data show that the learning of letter strings is affected by both the explicit strings used and also by the abstract (rule) structure used to generate a number of the surface-dissimilar strings. From such data, one can conclude that learners are sensitive to the rule structure underlying a serial pattern.
Restle (1970) came to the same conclusion, arguing that serial learning proceeds, not by the rote memorization of individual events and their order, but by the integration of "natural subparts" (p. 482). He hypothesizes that the learning of sequences which can be generated by simple hierarchical rule trees proceeds by the subject discovering the appropriate subunits, determining the relationships between them and then re-iterating this process, "forming higher and higher order structures until the entire serial pattern is constructed" (p. 487). The model is supported by the analysis of error data demonstrating that subjects experience greatest difficulty with parts of the pattern corresponding to the highest order rule transformation and correspondingly less difficulty with rules which appear lower in the tree. Thus, Restle suggests, subjects are responsive to the formal rule structure inherent in a set of information.

Jones (1976) has demonstrated that rule structure may not constitute the single greatest influence on pattern learning. Restle and other theorists who have emphasized the interval structure of serial patterns do not discuss the role of nominal pattern structure. They concentrate only on the formal character of the pattern and not on the perceptually salient characteristics (e.g., repetitions of a short string of characters) inherent in the same pattern. Jones (1976) systematically manipulated the nominal and interval properties of a set of serial patterns and found that those sequences characterized by regular nominal relations were reconstructed with much greater accuracy than were patterns lacking
such relationships. She also found that spatial presentation (a simultaneous display of all the to-be-remembered items) facilitated the recall of symmetrical patterns—patterns of the sort which can be generated from hierarchical rule structures. She concludes that "hierarchical sequences are primarily easier because they result in readily detectable structure at the nominal level" (p. 487) and that "Nominal structure appears easier to detect in spatial arrays..." (p. 487). These data point to the importance of surface features of a pattern—the regularities, repetitions and symmetries of strings of characters—and to their interaction with higher order, interval characteristics of rule structure inherent in a given pattern.

Using Hierarchical Computer Menus

A form of computer dialogue designed to guide users through often unknown action sequences is the menu. Although menu interfaces are not necessarily hierarchical, designers frequently choose to use menu selection dialogues to step users from general categories to specific categories using a succession of hierarchically nested menus. Three related areas of research on the design of such hierarchically nested menu systems will be discussed in this subsection. These areas are: the depth/breadth tradeoff, principles of organization, and navigating through hierarchical menu systems.

The depth/breadth tradeoff. Miller (1981) studied the effect that different forms of menu organization had on speed and accuracy of choosing a target. Using stimuli based on Dewey's hierarchical categorization scheme, Miller varied the depth (the number of menu
levels) and the breadth (the number of choices per menu) of the structures in which the target resided. He found that both acquisition speed and errors were optimized for the systems with intermediate depth (2 and 3 levels vs. 6 or 1 level) and breadth (4 and 8 choices vs. 2 or 64). The pattern of poor performance in the deep (two choices at each of six levels) and of enhanced performance in the two level, eight choice tree was confirmed by Kiger (1984). He found, in addition, that subjective preference was consistent with optimized performance in these structures. There is, however, some controversy over the poor performance of the 64 item, single level condition. Snowberry, Parkinson and Sisson (1983) noted that Miller's 64 item, single level condition had used data columns in which the items were drawn from different categorical groupings. They argued that breadth, in this condition was thereby confounded with a breakdown of the strict categorical grouping of display options which was characteristic of the rest of the conditions. They therefore used two different single level, 64 choices conditions. One of these had the location of items randomly determined. The second presented all category members in the same area of the display. They found, with strictly categorized data displays, that speed and accuracy both improved as a function of menu breadth. This pattern is consistent with an earlier study by Dray, Ogden and Vestewig (1981) which found that naive users were faster when using menus which presented all the material on one screen rather than with menus calling sub-menus.
Principles of organization. The role of categorically determined arrangement has itself been studied. Liebelt, McDonald, Stone and Karat (1982) studied the effect that arranging menus so that the terminal node members were in natural categories (Organized) or not (Random) had on people's ability to learn a three-letter response associated with each target item. They found that associating the response to meaningful choice points in the Organized structure resulted in more accurate performance than in the Random structure. This effect was replicated by this group (McDonald, Stone & Liebelt, 1983) in a later study which compared reaction times and errors to target for categorical, alphabetical and random orderings of 64 items. They found that categorical groupings outperformed alphabetical and random organizational forms. This finding seemingly contradicts that of Card (1982). Card (1982) looked at reaction times for selecting a menu for alphabetically, functionally (categorically), and randomly ordered command names. He found that alphabetical organization produced the fastest response times initially but that with large amounts of practice (800 selections from an 18 item list) the effects of the arrangement virtually disappeared. A number of differences between the experimental conditions make it difficult to assess what the impact of Card's data should be. Card used a smaller target list than most of the other studies reviewed in this section (18 vs. 64 items). His subjects were highly practised by the time the differences among the conditions disappeared. His subjects were novices and the list was composed of command names. They may well not have understood the basis for categorical assignment. This is in marked contrast to
the stimulus materials used by all of the others investigating the effect of categorization. Other investigators have used natural categories which should be well-known to the subjects. These variables need more systematic investigation.

Navigating through menus. Several investigators have noted that one of the problems with deeply nested hierarchical menu systems is that users tend to become 'lost' when they search. Two approaches have been suggested to deal with this problem. The first uses a pictorial representation of the hierarchy as an aid. Billingsley (1982) compared the effects of two different aids with an unaided control group on the efficiency of an information search task. One of the aids was a data map which showed the structure of the database with all descriptors and targets correctly portrayed. The other aid was a data index containing the alphabetized names of the targets and the sequence of menu choices which resulted in the target. She found that performance (both search time and search efficiency) was most enhanced by the pictorial aid. Parton et al. (1985) looked at problems which naive users have when learning to use a menu system. They compared the effectiveness of four different training conditions on later search performance and user assessment of ease of learning. One group was given a list of pathways for target attainment. A second group was given exposure to the menu frames. A third group was given a diagram representing the overall tree structure. The fourth group was allowed to use the system during the study period. All behavioral indicators showed the group receiving the tree structure to be best prepared.
Snowberry, Parkinson and Sisson (1985) also investigated the phenomenon of disorientation in search through an hierarchical menu system. They first analyzed in greater detail the results from their earlier study (Snowberry, Parkinson and Sisson, 1983). They found that over 50% of the errors made were in the first two levels of search. From this they hypothesized that the problem lay in the weak associations between broad descriptor terms and specific target words. They tested this by giving three different types of aids: one group was given the target on all screens; a second was given the preceding choice; the third was given the items nested between each of the alternatives on the present screen. They found that the group given the subsequent selections (the third group) outperformed all the other groups but that there were no significant differences between the first two forms of aiding and a control group. User preferences also supported the utility of aiding through the provision of subsequent selections.

The studies reviewed in this section illustrate the importance of two characteristics of a set of materials to be searched or remembered. First, they illustrate the impact of the formal, logical characteristics of information. People are able to recognize and use the formal relationships inherent in a set of information. Secondly, they show that the way in which such information is organized when presented to a person attempting to deal with that information can either facilitate or interfere with the use of that data, suggesting the great importance of presentation format.
From the literature review section, it can be concluded: (1) that individuals recognize structural orderings within a set of information; (2) that the form in which information is presented affects the ability of individuals to use that information; and (3) that memory is either affected by formal data structures or is itself structured. There is little behavioral data about the strategies subjects use to access information in information structures. The research which is to be described will investigate search strategy and some variables which may affect search strategies in hierarchical data structures.
METHOD

Approach

The literature review has demonstrated that hierarchies are thought to be an important kind of information or data structure. People are aware of such structures, they spontaneously use hierarchical structures, and are influenced in their choice procedures by hierarchical structures. However, we have little direct study of strategies people use when searching hierarchies. Most studies of search use materials which can be organized into hierarchical structures and which have been so organized by the experimenter. We assume that subjects' mental structures match that described by the experimenter. Search strategies are most often derived from indirect measures like response time and errors. Although these are very effective measures they do not provide a direct view of search strategies per se.

The research to be described in the sections which follow looks directly at search strategies by examining the patterns of choices made by individuals searching visually depicted hierarchies. It examines searching under minimal information. Rather than searching in a hierarchy made up of known concepts, subjects are asked to search an abstract hierarchy. The major reason for so doing was to ensure that the search patterns studied would be influenced solely by the physical characteristics of the hierarchy, the branch and
level structure, and not by the subject's knowledge of the conceptual structure underlying the knowledge structure used. The task chosen is also a reasonable but abstract representation of a real search task. In the real world, hierarchies which are searched generally represent well-known concepts. This is, of course, not always true. If the searcher is looking for information in a field which is technically complex and which is not within the searcher's field of knowledge, he does not know the conceptual relationships between the superordinate and subordinate concepts of the data structure. Therefore he is engaged in a search task which is approximately equivalent to that faced by the subjects in this study.

A non-directive task was used. The subjects search until they reach a target without feedback other than feedback about whether the node chosen is the target. Subjects thus had the freedom to structure or not to structure their search. The presence of structure in search is the primary topic of interest. The effect of two experimental variables—systematic vs. random labelling of the information display and the provision of a technique for reducing memory load—on search systematicity is also investigated.

Procedure

To ensure that a sufficient amount of data was collected for data analysis purposes, there is a distinction between the task as described to the subject and that determined by the experimenter. These will be described separately.
The task was described to the subject in the following way: Each subject was presented with a hierarchy labelled with alphanumeric characters (cf. Fig. 1). The subject was told that one of the nodes in the data structure was the target, i.e., that it was his task to locate the node. He was told that the target was randomly chosen and that it was almost certainly different for each of the structures to be searched. He was to indicate each potential target by reading aloud the alphanumeric characters used as the node’s label. The experimenter wrote down the label and informed the subject about the correctness of his choice. If the node chosen was not correct, the subject was told to choose another node and to keep choosing nodes until he was informed by the experimenter that the target had been chosen. If the choice was correct, the subject proceeded to the next data structure. All subjects were advised to try to refrain from choosing a node within a single structure more than once. No penalty was attached to so doing. This procedure was repeated for ten data hierarchies.

From the experimenter’s point of view a slightly different task was being carried out. Thirty data points per hierarchy were needed to provide a stable base for data analysis. To make it less apparent that the subject was in fact simply generating a fixed quantity of data and to enhance the reality of the search task as described to the subject, a variable number of choices past this point were requested. The procedure was repeated until some number between thirty and forty choices were made for each hierarchy searched. The first thirty choices were used in the data analysis.
Figure 1. A Typical Stimulus Hierarchy
For the data analysis, it was assumed that subjects would adopt a consistent strategy for each 30 choice sequence. It was further assumed that subjects could and would be free to change strategies between hierarchies.

Subjects

Forty undergraduate students enrolled in introductory psychology at the Ohio State University served as volunteer subjects to fulfill a course requirement. Each was tested individually.

Design

Half of the subjects were told to cross off each chosen node. This is referred to as the "aided" condition. The other half were not allowed to indicate their past choices on the stimulus display or on any other record. This is referred to as the "not aided" condition. This condition was introduced to test the hypothesis, suggested by Rouse's (1978a,b) finding that search systematicity could be influenced by helping subjects to focus on solution paths which had not been eliminated by previous choices.

Half of the subjects were presented with hierarchies in which the physical form of the data structure and the labels used were congruent and meaningful. For example, the first node to the left at level one of the tree was labelled X1 and the nodes logically and physically subordinate to it were labelled X1,1; X1,2; X1,3; and X1,4 respectively. This is referred to as the "systematically
labelled" condition. The other half of the subjects were presented with hierarchies which used the same form but for which the labels used were randomly rearranged. These subjects were in the the "randomly labelled" group condition.

There were, therefore, four groups of ten subjects each. There was the group which had systematically labelled data structures and aiding. The second group had systematically labelled data structures and were not aided. The third group had the randomly labelled data structures and aiding. The fourth group had the randomly labelled data structures and were not aided. Subjects were randomly assigned to one of these groups.

Data Evaluation Methodology

The basic data recorded consisted of the sequence of 30 nodes chosen by a subject on each of ten search attempts. The goals of the data evaluation procedures used were: (1) to categorize the search strategies used by the subjects and (2) to investigate the effect that the experimental conditions had on the subjects' tendencies to search systematically. The first step in categorizing search strategies was to utilize the behavior of computer programs simulating search behavior consistent with a set of proposed models for search to find measures which distinguished the models. Then, the subjects' behavior was compared to the predictions of the models on these measures in order to identify the model or models which best described their behavior. Once procedures were identified, the subject data were used to test the effects of the experimental
conditions on the tendency to search randomly vs. systematically. Because the data analysis procedures are unique to the present research, they are described in detail in the following paragraphs.

In order to adequately describe the methods used to evaluate the data two sets of definitions will be provided. The first describes the notion of set membership which underlies the evaluation methodology used. The second defines the classes of models used for data comparison.

**Set membership.** Basic to all of the categorization analyses is the notion that any sequential pair or longer sequence of choices can be categorized based on their membership in a small number of pre-defined sets. The sets used in the analyses are defined as follows:

(a) Within a branch

Every data hierarchy consisted of fifteen branches. A branch is defined as the set of nodes which includes one node at Level 1 and the four nodes which are linked to that node at Level 2. In the standard hierarchy, for example, the five member set \{A1; A1,1; A1,2; A1,3; A1,4\} is defined to be a single branch. No order relationships were defined among set members or among sets. Any sequence of responses can be categorized as within a common branch or not.
(b) Within a level

In the analyses of level characteristics the 75 nodes of the standard hierarchy were considered to be divided into two sets. One set was composed of the fifteen data points \{A1; A2; A3;...;A15\} and is referred to as Level 1. The second set was composed of the nodes at the lowest level of the hierarchy. This set, referred to as Level 2, consisted of the members \{A1,1; A1,2; A1,3;...;A15,4\}. No order relationships were defined among set members or among sets. Any sequence of responses can be categorized as within a common level or not.

(c) Different branch and level

This set type was used only in the first of the categorical analyses to be described in the next section, the transition analysis. If two consecutive choices belonged neither to the same level nor to the same branch, they were considered to belong in this category.

It should be noted that this description of branch and level sets uses the standard hierarchy as a model. In the standard hierarchy, the physical form and the labels used to define nodes for that form are congruent. That is, the first node at Level 1 is labelled in a way which identifies it as in the hierarchy (e.g., A,B,C, etc.) and which says that it is the first node on the left of the form (e.g., A1). The nodes nested under each of the Level 1 nodes are similarly systematically arranged. Branches located to the right of this branch are numbered relative to the first branch (e.g., A2, A3, etc.). However, as pointed out earlier, half of the subjects had
the labels randomly rearranged so that it could be determined if choice strategies were based on the labels or on the physical form of the hierarchy. The data from these subjects were submitted to two separate analyses. The first analysis used sets defined by the labels as the reference set. In the Results section, this will be referred to as the data which used labelling as the reference dimension. The second analysis used the sets defined by the node labels on the randomly relabelled hierarchies as reference sets. For this analysis, the reference set depended on which label had been assigned to which node by the randomization procedure used. Because sets correspond to those determined by the physical location of the node rather than its label, the analysis in the Results section refers to this as the data which used form as the reference dimension.

Search models. Three classes of models were considered. The first assumes that search is random and that choices are not dependent on the physical characteristics of the data structure used. This is referred to as the random model for search. The second class of models hypothesizes that the subjects' search patterns are based on the logical characteristics of a hierarchical data structure. They further assume that once a search set has been chosen, all nodes in the set will be chosen before the searcher chooses another set. This class is referred to as exhaustive search. The third class of models suggests that search is related to the logical characteristics of the structure but that subjects 'sample' a number of nodes within a set and move to another set
usually before exhausting all possible choices from the chosen set. This class is referred to as sampling search. Extensive verbal descriptions of these models are provided in Appendix A, Part 1. Algorithms for calculating the search paths associated with each of the models are provided in Appendix A, Part 2. It must be pointed out that the sampling models tested were intended as representative of a class of models rather than as strict descriptions of behavior. Thus, different parameters could have been used to define the minimum number of nodes sampled per set sampled or the probability of maintaining choice within a set once sampled.

Both the exhaustive and sampling models were more finely analyzed. The formal description of a node in the two level hierarchies used is made up of at least two parts. One identifies the branch in which the node is resident. The second identifies the distance of that node, in intervening nodes, from the node of origin for that tree. For example, the node labelled A1.4 can be identified as a member of the branch A1 and is further identified as being at Level 2 of the tree because it has a value (4) after the comma. To continue the explanation, if there had been a third level to the tree, the notational form would be A{x,y,z}.

Reference sets for the data analyses were defined either in terms of the branch characteristic of the node or the level characteristic of the node. The models for both exhaustive and sampling searches, therefore, were defined to be determined by either the branch or the level description of the data structure. This results in five models to be evaluated: random, branch exhaustive, level
exhaustive, branch sampling and level sampling. Each was coded into a Fortran program that simulated the behavior of a subject in searching a hierarchy. The output of each simulation was a sequence of node choices resembling the data provided by each subject who performed the experimental task. The programs used to generate the model data appear in Appendix A, Part 3.

Hypotheses

(1) that subjects will tend not to behave in ways consistent with the random model even though task efficiency is not enhanced by adopting any of the more systematic models;

(2) that, consistent with the importance of nominal data features (cf. Jones, 1976), subjects will tend to adopt strategies consistent with the physical format of the data structure rather than with the logical labelling;

(3) that subjects presented with forms in which the usual physical format and logical labelling are in agreement will be more likely to adopt exhaustive search strategies than subjects for whom the labelling and format are not in agreement; and

(4) that aiding will enhance subjects' tendencies to search systematically (cf. Rouse, 1978a,b).
Data Analysis

The data analysis had two parts. First, it was necessary to determine what was to be counted and the analysis to be done on the counted entities to provide a reliable method for data categorization. The goal of this part of the analysis was to produce a method for categorizing the data which was associated with the predictions from the formally defined search models. The second part of the data analysis was concerned with relating the distribution of categorized data to the experimental conditions which differentiated groups of subjects.

Categorical Analyses

Two separate analyses were conducted to identify a basis for assigning data to meaningful categories. The first analysis is referred to as the transition analysis. This method was suggested by Payne (1976) who was studying information processing strategies used in decision making. Payne's subjects were asked to choose an apartment for themselves based on information provided about each apartment. The number of dimensions of information available (e.g., noise level, size, cleanliness, etc.) and the number of alternative apartments were varied. In addition to analyzing decision effectiveness, Payne analyzed his subjects' search patterns in terms of the number and pattern of changes both within and across dimensions, a task analogous to that of this dissertation. This dissertation is looking for patterns of behavior which could reveal something about subjects' search strategies. There was a set number
of choices and dimensions (e.g., branches) along which those choices could vary. Thus, the first categorization analysis used pairwise shifts within the dimensions, which will be referred to as "transitions", as the measurement unit.

The second analysis is referred to as the runs analysis. This method used uninterrupted sequences of consecutive choices ("runs") as the underlying measurement unit. This measurement method was not taken from the literature but rather was arrived at through consideration of what would constitute a meaningful measure given the nature of the phenomena under consideration. Since different models predicted that subjects should make differing numbers of choices within a set, these differences should be reflected in the number of consecutive choices or run length within the set.

**Transition analysis.** The first measure identified was transition type. This measure examined the set membership features of each two successive data points for the thirty node choices used as data for each hierarchy searched. Three types of pairwise transitions were counted. These were: (1) transitions in which both pair members were within the same branch of the hierarchy; (2) transitions in which both pair members were at the same level of the hierarchy; and (3) transitions for which the two pair members were neither within the same level nor within the same branch. It should be noted that a given pairwise transition could very easily be counted in both of the first two transition types. For example, the set \{A1,1; A1,2; A1,3\} would be counted in both within branch and
within level transition type counts. These two types are not mutually exclusive.

So that patterns of searching could be identified, class indicators were established. In this analysis, data from the exhaustive models is deterministic along the dimension relevant to a given model. Therefore, exact predictions for the number of pairwise transitions possible within a 30 choice sequence can be made and these can serve as class indicators for the two models. Two search patterns are theoretically possible in a level exhaustive search. In any series of thirty consecutive choices, the choices could all be at the second level, giving the maximum number of transitions at Level 2 of the hierarchy, 29. If the choices began at the first level of the hierarchy and after choosing all 15 nodes at the first level, moved to the second level of the hierarchy, the maximum number of within level transitions in 30 choices would be 28. This line of reasoning suggested that the level exhaustive model was indicated if there was a pattern of 28 or 29 of a possible 29 within level transitions in a 30 choice sequence. The branch exhaustive search was similarly determined. For any thirty choice sequence, behavior consistent with this search model would serially and exhaustively make choices from six five-member branches. In this way, the branch exhaustive model was indicated by 24 within branch transitions for the thirty node choice sequence. Indicators for the transition types not relevant to the dimension defining each of these two models were derived from fifty runs of a program which simulated choice behavior under the rules defining these models (cf. Appendix A, Part 3).
The three remaining models, random, branch sampling and level sampling, are all at least in part probabilistic. Therefore, transition type indicators for these models had to be characterized by both a measure of central tendency and an indicator of variability. To estimate these measures, programs were constructed which produced behavior under the constraints described for the random and sampling models. The means number of transitions of the within branch, within level and different branch and level types and the standard deviations associated with fifty sample runs for each of the models were calculated.

**Runs analysis.** The second measurement unit used to differentiate search strategies counted uninterrupted sequences of consecutive choices (runs) within a reference set. The major distinction between the transitions analysis and the runs analysis is that the transitions analysis looked the type of shifts between all pairs of responses within the 30 choice sequence and assigned each pair to one or two transition types. The runs analysis looked at the lengths of sequences of responses within a 30 choice response sequence and assigned them to run length categories within a branch or level. Two independent counts were made of each data hierarchy for both model and subject generated data. One count used the branch sets as a reference. The second used the levels as reference.

To make the explanation more intelligible, the procedure used in generating the branch counts will be described. A similar analysis
was made of the level data. Beginning with the first node chosen for a given trial, each successive node was examined to determine if it were a member of the same branch set as the preceding node or nodes. When the succeeding node was from a different branch, the preceding nodes were counted and this number determined which run length category the run was to be attributed to. If, for example, a subject made the following sequence of node choices: \{A1; A1,1; A1,3; A2; A3; A3,1\}, he would be attributed with one count in the Branch Length 3 category, followed by one count in the Branch Length 1 category, followed by one in the Branch length 2 category. A similar procedure was applied to the data using for comparison the reference sets defined as Level 1 and 2.

Frequency counts were prepared for each hierarchy. Counts for each hierarchy fell into the following categories:

- **Branches:** Run lengths 1, 2, 3, 4, 5
- **Level 1:** Run lengths 1, 2, 3, . . . , 15
- **Level 2:** Run lengths 1, 2, 3, . . . , 30

There were ten frequency distributions for each of the subjects, one derived from each set of 30 choices for each hierarchy searched. To ensure a stable base for comparison, the programs developed from the theoretically derived search models generated 200 sets of 30 choices each.

To aid in interpretation of the data, the frequency distributions prepared above were compressed. The branch frequency distribution used contained three categories. The first category contained the
number of runs of run length 1. Next the totals for cells corresponding to run lengths 2, 3 and 4 were added together to become the second branch run length category. The frequency for run length 5 became the final category.

The frequency table constructed for the analysis of the count of the data using the level characteristics as reference also contained three categories. The categories were defined as follows:

Category 1—Levels 1 and 2, run length 1 and 2;
Category 2—Levels 1 and 2, the totals of run lengths 3 to 14 and Level 2, the totals of run lengths 16 to 29; also included were cases in which there was one but not two run lengths of 15;
Category 3—Levels 1 and 2, run length 15 or Level 2, run length 30.

The first row of both tables will be referred to as the short run length category, the second as the intermediate run length category, and the third as the exhaustive run length category.

These groupings were chosen to reflect meaningful categories for the hypothesized search models. Frequency differences between the shortest run lengths and intermediate lengths differentiated the strategies of the random and sampling models. The third category was almost exclusively associated with the exhaustive models.

The goal of these counting procedures was to find indicators which could be used (1) to differentiate the models in a statistically valid way and (2) to compare the overall subject data with the proposed models. If all the run length frequency data for a hierarchy were used to assign the choices in any given 30 choice
sequence to a model, it would be impossible to estimate the type and degree of interdependencies within the data. This is because the presence of a run of any given length affects the possibility of occurrence of runs of other lengths. In order to assure that the categories to be used in later chi square analyses were independent, it was necessary to choose a single indicator from any set of 30 choices which could be used to assign that 30 choice set to a single category. It was decided that this would be the run length category which had the greatest number of runs. This is referred to as the dominant run length category. Each 30 choice sequence was assigned to the categories described in the paragraphs preceding this one.

The categorized data show the expected differences among the models. This is illustrated in Table 1 which shows the frequency distribution of branch and level runs by run length groupings for the model-generated data.

Table 1
Distribution of Dominant Run Length Categories for the Model Data

<table>
<thead>
<tr>
<th>Model</th>
<th>Branch run lengths</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
<td>Intermediate</td>
<td>Exhaustive</td>
<td></td>
</tr>
<tr>
<td>Random</td>
<td>200</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Branch Exhaustive</td>
<td>0</td>
<td>0</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>Branch Sampling</td>
<td>0</td>
<td>200</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Level Exhaustive</td>
<td>200</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Level Sampling</td>
<td>200</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Level run lengths</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
<td>Intermediate</td>
<td>Exhaustive</td>
<td></td>
</tr>
<tr>
<td>Random</td>
<td>177.5</td>
<td>22.5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Branch Exhaustive</td>
<td>186.5</td>
<td>13.5</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Branch Sampling</td>
<td>191</td>
<td>9</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Level Exhaustive</td>
<td>0</td>
<td>0</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>Level Sampling</td>
<td>20</td>
<td>176</td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>
This table shows that the distribution of run length data is consistent with the general form of the proposed search models. The exhaustive and sampling models differ as predicted on the dimensions appropriate to each model. So, for example, the branch exhaustive, branch sampling and random models all differ in the branch run length categories with which they are most strongly associated although they do not differ in the level run length distribution. A similar effect is shown for the level related models in the level run length distribution. This suggests that the dominant run length categorization scheme is a sensitive enough tool to discriminate the categories under investigation.

A problem, however, arises when the data are interpreted using this scheme alone. The data in these tables considered individually give the impression that there is a good deal of randomness in the dimension (branch or level) not used as the basis for the choices implied by a given search model. For example, the branch models appear to be random on the level dimension. This is acceptable in dealing with the model data because we know the relevant dimension for a given model from its labelling. When attention is turned to the data from individual subjects, we cannot know the "relevant" dimension. It is the task of the analysis to determine what is the relevant dimension.

To provide further insight into the nature of the relationships analyzed here, a second condensation technique was devised. Rather than two independent tables, one for branch and one for level data, the data was retabulated as cross-classified data. The dominant run
length categories for the branch and run length dimensions were
determined separately. A table was then prepared which had the
dominant run length category distribution for the branch data as the
row dimension and the dominant run length category distribution for
the level data as the column dimension. The data from each
hierarchy (set of 30 choices) was assigned to the appropriate cell
of the table. The cross-classified data are shown in Tables 2-6:

Table 2
Distribution of Dominant Run Length Categories
for the Random Model

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
<th>Short</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td></td>
<td>173</td>
<td>27</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td></td>
<td>0</td>
<td>0</td>
<td>X (1)</td>
</tr>
</tbody>
</table>

Table 3
Distribution of Dominant Run Length Categories
for the Branch Exhaustive Model

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
<th>Short</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td></td>
<td>180</td>
<td>20</td>
<td>X</td>
</tr>
</tbody>
</table>

1. It was both logically and practically impossible that data could fall into
the category of Exhaustive by both Level and Branch run criteria.
Table 4  
**Distribution of Dominant Run Length Categories for the Branch Sampling Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>188</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 5  
**Distribution of Dominant Run Length Categories for the Level Exhaustive Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>0</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 6  
**Distribution of Dominant Run Length Categories for the Level Sampling Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>16</td>
<td>180</td>
<td>4</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

These data suggest that in the cross-classified table there is a cell which is most strongly associated with each of the models. Table 7 places the name of each of the five models in the cell of the cross-classified table which accounts for most of its occurrences in the model data.
Table 7
Model Names and the Dominant Run Length Categories with which each is Most Strongly Associated

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short random</td>
<td>Short level sample</td>
</tr>
<tr>
<td>Intermediate branch sample</td>
<td></td>
</tr>
<tr>
<td>Exhaustive branch exhaustive</td>
<td></td>
</tr>
</tbody>
</table>

The distribution of runs outside of the category most strongly associated with a given model can be used to provide estimates of classification error.

Hypothesis Testing

Once a basis for categorical assignment relatively free from the effects of uninterpretable confoundings had been identified, the second phase of the data analysis could be performed. The specific questions which remain to be tested are:

Did the subjects presented with a conceptual separation between physical form and labelling choose to follow the logical labels or the physical form of the data structure?

Did random labelling make subjects more or less systematic in their choice patterns?

Were the subjects given aiding more or less systematic than those who were not given aiding?
The testing of the last two hypotheses required that the distribution of categories be related to the question of search systematicity rather than model identification. Since it was the systematic nature of response rather than models per se which was in question, values for both types of exhaustive searching and for all types of sample searches were grouped together. This is discussed in more detail in the Results section.

**Form vs. labels.** A two step process was used to determine whether subjects in the randomly labelled groups used the labels or the form (physical arrangement) of the data structure to guide their choices. The first step was to compare the categories gotten by analyzing the choice sequences using form as a reference set with those gotten by using labelling as a reference set to determine if the categorical assignments made using the two reference methods were different. The statistic used to test this was the kappa statistic (Fleiss, 1981). If this statistic showed the categorical assignments made using form and labelling to be different, the second step would assess if the distribution of categories produced by either method of choosing was different from random.

**Labelling and aiding.** The last two hypotheses were evaluated using the chi square statistic. The distributions of the data which fell into the categories usually associated with the random, sampling and exhaustive search strategies were compared between the groups who were aided and those who were not aided. A similar analysis was performed comparing the distributions of random,
sampling and exhaustive search strategy categories across the randomly labelled with the systematically labelled groups.
RESULTS

Categorical Analyses

Transition analysis. The three transition types identified for examination were transitions within a branch, transitions within a level, and transitions which were between both different levels and branches. The first type is used to separate the branch models from the level and random models and to distinguish the branch exhaustive from the branch sampling models. The second type was to distinguish the level models from the branch models and the level sampling from the level exhaustive models. The different branch and different level transition acted as an identifier of the random model and to some extent confirmed the distinctions between the sampling and exhaustive models for both branch and level dimensions.

The mean numbers of transitions within the three transition types for the fifty simulated data runs per model are given in Table 8. The standard deviations are given in parentheses.
Table 8

Means and Standard Deviations for Transition Type Indicators for Data from the Model Simulations

<table>
<thead>
<tr>
<th>Model</th>
<th>Within Branch</th>
<th>Transition Type</th>
<th>Within Level</th>
<th>Different Branch &amp; Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>1.50(1.1)</td>
<td>18.54(2.56)</td>
<td>9.62(2.45)</td>
<td></td>
</tr>
<tr>
<td>Branch exhaustive</td>
<td>24.00(0)</td>
<td>17.74(1.07)</td>
<td>1.66(0.99)</td>
<td></td>
</tr>
<tr>
<td>Branch sampling</td>
<td>18.36(1.1)</td>
<td>17.96(2.07)</td>
<td>3.50(1.50)</td>
<td></td>
</tr>
<tr>
<td>Level exhaustive</td>
<td>1.14(1.2)</td>
<td>28.50(0.50)</td>
<td>0.46(0.50)</td>
<td></td>
</tr>
<tr>
<td>Level sampling</td>
<td>0.78(0.9)</td>
<td>23.94(1.90)</td>
<td>4.76(1.72)</td>
<td></td>
</tr>
</tbody>
</table>

The analysis of the model data reveal the anticipated pattern of results. A most disturbing feature is the overlap among distributions about the mean, for the level data in particular.

The data from the forty subjects were analyzed with regard to the transition patterns. A great deal of the subject data fails to fall within two standard deviations of the mean for all three transition types associated with any of the models. Only 31.5% overall (range: 24-35% over the four experimental groups) met the criteria for model identification on all three transition types. This suggests that some more complicated processing than that assumed by the theoretical models used is going on. To make as much of the data as possible and because the investigation was interested more in identifying behavior consonant with classes of models rather than in the specific models used, it was decided to loosen the criteria for model identification. The choices identified by a given 30 choice sequence were assigned to a model based on the following set of criteria: Level exhaustive was assigned if there were 28 or 29 transitions in the level transition category. Branch exhaustive was assigned if there were 24 transitions in the branch transition
category. Random was assigned if the data fit within two standard deviations of the mean for the random model on all three dimensions. Level sampling was assigned if the subject's data fell within two standard deviations of the mean for the level sampling model along the level transition category. Branch sampling was assigned if the subject's data fell within two standard deviations of the mean for the branch sampling model on the branch dimension. Branch and Level (Both) sampling was assigned if the data met both of the preceding conditions. If the data did not meet any of the preceding conditions, it was assigned to the unknown category. The distribution of categories is given in Table 9.

Table 9

<table>
<thead>
<tr>
<th>Experimental group</th>
<th>Exhaustive</th>
<th>Sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Random</td>
<td>Branch</td>
</tr>
<tr>
<td>Systematic label, aid</td>
<td>7</td>
<td>24</td>
</tr>
<tr>
<td>Systematic label, no aid</td>
<td>1</td>
<td>29</td>
</tr>
<tr>
<td>Random label, aided</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Random label, no aid</td>
<td>0</td>
<td>6</td>
</tr>
</tbody>
</table>

It was found that 61.25% of the data could be easily categorized as either exhaustive or random. Much, although, not all of the remaining data fit the requirements for the sampling models. Several problems remained. First, 7.5% of the data was impossible to classify. This might have been because, in principle, the models were not differentiable (for evidence of this, see the overlap between the distributions of the level sampling and random models in
Table 8) or because the measure used was insufficient to distinguish among the models. Second, assignment to categories was based, in most cases, on a single transition type value. Very often the rest of the values were not in accord with the values given in the simulated model data. This may have been due to insufficiencies in the models (i.e., the subjects' behaved in ways more complex than that suggested by the models) but this analysis contributed little to our understanding of the reasons for these discrepancies. Third, the three transition types were used as independent indicators of a search hierarchy's classification. However, the measures were not independent since any transition may contribute to both within branch and within level transition count. These deficiencies caused us to look for other more meaningful and statistically independent things to count.

Runs analysis. Frequency distributions of runs of all possible lengths were prepared for all ten hierarchies for each of the forty subjects. The distributions were compressed into the three run length categories used for comparison for each of the branch and level dimensions. The dominant run category for level and branch dimensions was determined for each set of thirty choices. These were tabulated in the same two-way table which used branch and level as column and row dimensions that was used to tabulate the model data (cf. for example, Tables 2-6).

When these data were fitted to the two-way tables used for the model data in the Method section, a fourth row and column were suggested.
In the model data, it had happened, on occasion, that there were the same number of runs in two run length categories. Originally these ties had been resolved by assigning half the value of that data point to each of the contending categories. However, the tie state was more frequent in the subject data than in the model data and seemed to represent, for the most part, a meaningful category. The most frequent instance of this new category was a tie between the short and intermediate run length categories for the level data. This occurred most frequently in cases in which the subjects were using a branch exhaustive strategy. The original data indicated that this pattern of results was strongly associated with the following type of response pattern: \{A1; A1,1; A1,2; A1,3; A1,4\}. That is to say, the subject first chose the level one member of the branch selected then exhaustively chose the level two members of the branch and proceeded to some other branch and chose set members in an analogous manner. The result of this pattern of choices over the 30 choice sequence collected for each hierarchy was that the subject would choose six short level runs (i.e., runs of length one at the first level) and six intermediate level runs (i.e., runs of length four at the second level). Because this category represented meaningful patterns in the data, it was decided to include it in the analysis even though categorization based on patterns observed post-hoc complicate the statistical evaluation of the data.

The dominant run length data for the models and the subjects were recategorized including the new, fourth category. Tables 10-14 show
the results of this reanalysis, first for the model data and then for the subject data.

Table 10  
**Distribution of Dominant Run Length Categories for the Random Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
</tr>
<tr>
<td>Short</td>
<td>173</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 11  
**Distribution of Dominant Run Length Categories for the Branch Exhaustive Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
</tr>
<tr>
<td>Short</td>
<td>0</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>180</td>
</tr>
</tbody>
</table>

Table 12  
**Distribution of Dominant Run Length Categories for the Branch Sampling Model**

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
</tr>
<tr>
<td>Short</td>
<td>0</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>188</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 13
Distribution of Dominant Run Length Categories for the Level Exhaustive Model

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 14
Distribution of Dominant Run Length Categories for the Level Sampling Model

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>16</td>
<td>8</td>
<td>172</td>
<td>4</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

A comparison of these tables with the tables in the Method section shows very little difference in the implications of these data for identifying cells in the joint table which are, in the model data, closely associated with the models. That table now becomes:
Table 15
Model Names and the Dominant Run Length Categories with which each is Most Strongly Associated

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
</tr>
<tr>
<td>Short</td>
<td>random</td>
</tr>
<tr>
<td>Tie</td>
<td>branch sample</td>
</tr>
<tr>
<td>Intermediate</td>
<td>branch exhaustive</td>
</tr>
</tbody>
</table>

A visual inspection of the subject data reveals considerable variability in the distributions of dominant run length data over the categories in the cross-classified table. This is demonstrated in Tables 16-19.

Table 16
Distribution of Dominant Run Length Categories for the Systematically Labelled, Aided Subjects

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
</tr>
<tr>
<td>Short</td>
<td>7</td>
</tr>
<tr>
<td>Tie</td>
<td>1</td>
</tr>
<tr>
<td>Intermediate</td>
<td>6</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>2</td>
</tr>
</tbody>
</table>
Table 17
Distribution of Dominant Run Length Categories for the Systematically Labelled, Non-Aided Subjects

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>4</td>
<td>1</td>
<td>11</td>
<td>35</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>2</td>
<td>27</td>
<td>1</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 18
Distribution of Dominant Run Length Categories for the Randomly Labelled, Aided Subjects

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>18</td>
<td>12</td>
<td>46</td>
<td>5</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>6</td>
<td>0</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>5</td>
<td>0</td>
<td>1</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 19
Distribution of Dominant Run Length Categories for the Randomly Labelled, Non-Aided Subjects

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>3</td>
<td>1</td>
<td>25</td>
<td>31</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>8</td>
<td>3</td>
<td>6</td>
<td>14</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>X</td>
</tr>
</tbody>
</table>

The data which fall into the five cells identified most strongly with the models account for 67% of the subject data. A relatively large proportion of this falls into the cell most strongly identified with the level exhaustive model. The cell associated
with the level sampling model also accounts for a good deal of data. One interesting pattern in the data across all of the experimental conditions is the relatively small number of cases in which the subject data falls into the joint dimension short run length category characteristic of truly random searching according to the model. This supports the first hypothesis proposed in this dissertation—namely, that subjects in this situation do not adopt random search behavior even though the task neither explicitly calls for nor, in a statistical sense, is made more efficient by the adoption of some systematic strategy.

There is a reasonable amount of data in categories not covered by the five proposed models. However, the data which did not fall into the five cells that are most strongly associated with the specific models tested can be interpreted using as a reference the dimensions used in Tables 10-14 and 16-19 to structure the data. The data displayed in Tables 16-19 provide evidence that the subject data is drawn from (internal) models which are not as simple and clear-cut as those embodied in the statistical models used as reference points. The models generated behavior that was governed by the rule that only the dimension dictated by the model in question (branch or level) was relevant and that the other dimension was irrelevant. They enforced this assumption by randomizing the members of a branch or level set before choosing from it. Therefore, in the model data, the cell characteristic of a given model is in the appropriate row/column relevant to one dimension but in the column/row
associated with a random pattern (i.e., the short run lengths) for the other.

The subject data suggest that real search is more complicated than the models underlying our simulation. The subject data appear to be affected by more than one dimension of the data structure. Many subjects will search exhaustively on one dimension while at the same time showing some structured search in the second dimension. This is shown by the presence of the intermediate run length category in the column associated with exhaustive level run lengths and of tie and intermediate run length data in the row associated with exhaustive branch run lengths. Thus, an important pattern in the subject data is the relatively large number, especially in the case of the branch dimension, of responses which show behavior consistent with an exhaustive search strategy along one dimension and also show some systematic pattern along the other dimension.

Table 20 serves a double purpose. First, it further illustrates the effect discussed in the preceding paragraph. Second, it shows the degree to which the two classification schemes agree on the identification of models with subject data.
Table 20
Correspondence Between the Categories Produced by the Transition and
that Produced by the Runs Analyses for all Subject Data

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>6R;20?;2LS;</td>
<td>13LS;1BS;</td>
<td>65LS;22LE;</td>
<td>10;LE</td>
</tr>
<tr>
<td></td>
<td>3BE;1SBoth</td>
<td>1SBoth;1R</td>
<td>2SBoth;1R</td>
<td></td>
</tr>
<tr>
<td>Tie</td>
<td>1?</td>
<td></td>
<td>2SBoth;1LS;</td>
<td>1LE</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1LE</td>
<td></td>
</tr>
<tr>
<td>Intermediate</td>
<td>14BS;67;2LS;</td>
<td>2LS;4LE</td>
<td>5SBoth;3LS;</td>
<td>41LE</td>
</tr>
<tr>
<td></td>
<td>1SBoth</td>
<td></td>
<td>2LE</td>
<td></td>
</tr>
<tr>
<td>Exhaustive</td>
<td>7BE;4BS</td>
<td>51BE;1SBoth</td>
<td>3BE;2PS</td>
<td>X</td>
</tr>
</tbody>
</table>

Code:
Categories used in the transition analysis:
R=Random; BE=Branch Exhaustive; LE=Level Exhaustive; BS=Branch Sampling;
LS=Level Sampling; SBoth=Sample both branch and level; ?=unknown

The underlined values in the table represent data in the categories
defined by the transition analysis which are in the cell most
strongly associated with the same model in the branch runs analysis.
Inspection of the table reveals that much but not all of the data is
categorized in the same way by the two categorization methods. Some
of the differences are attributable to deficiencies in one or the
other of the categorization methods. For example, the 22 Level
Exhaustive data points which appear in the Short branch
length—Intermediate run length category are for the most part
attributable to deficiencies in the definition of the Level
Exhaustive category in the transitions analysis—there were ways of
producing a pattern of 28 or 29 within level transitions other than
either remaining within a the first level until it was exhausted and
then switching to the second or remaining within the second level.
for all 30 choices. Other deviations from the cell identified most strongly by the model reflect the same features of the data that are shown in the runs analysis. Most of the data categorized as Branch Exhaustive and a good deal of the data categorized as Level Exhaustive fell into the categories which indicated that subjects were using more than one dimension of the data structure to base their search strategy on. This trend is both interesting and important for our understanding of the subjects' behavior.

The second hypothesis stated that subjects will tend to adopt strategies consistent with the physical format of the data structure when the logical labelling is not in accord with the physical format. This hypothesis could only be tested in the two subject groups for whom the labels of the nodes on the hierarchies used as stimuli did not reflect the logical structure of the data structures. The branch and level run patterns in these data were analyzed twice using two different reference sets. One analysis defined the logical labels as the reference. Therefore, a typical branch set was defined as \{A1; A1,1; A1,2; A1,3; A1,4\}. The other analysis defined as a set the labels which had been randomly assigned to the nodes which were physically attached to the nth node of the structure used. For this analysis, the reference set for the same branch might be \{A3,1; A15; A4,3; A1,2; A3,4\} or any set of node labels depending on which label had been assigned to which node by the randomization procedure used. If the subject had chosen to use the structure given in the labels, the analysis based on the labels should show a pattern of longer (i.e., intermediate and
exhaustive) run lengths. If, conversely, the subject had chosen to use the structure given in the physical structure, the analysis based on the form should show a pattern of longer (i.e., intermediate and exhaustive) run lengths.

In order to be able to state that subjects used either form or labelling to structure their search strategies, it was necessary to ensure that the patterns of categorical assignment produced by the two judgement methods were not the same. This was done by testing the dominant run length category distributions for the form and label analyses for independence using the kappa statistic. The kappa statistic is a measure of agreement for categorical data which corrects for chance agreement based on the marginal proportions (Fleiss, 1981). The kappa values for the agreement between the form and label run distributions on the branch and on the level dimensions for both the aided and non-aided randomly labelled groups were not significantly different from chance. The results of the kappa tests confirm that the categories assigned using form as a basis for categorization are different from those which use labelling as a basis for categorization. These methods for category determination are different.

This research separated the dimensions of form and labelling by randomly reassigning the labels on the hierarchies given to half the subjects. If subjects used only one dimension to structure their choices, categories based on the dimension not used should be equivalent to those produced by the random model. Therefore, the second step in the analysis was to determine if the choice
patterns based on either form or labelling was different from those produced by the random model. The following tables show the data which are to be tested. (2)

Table 21
Distribution of Dominant Run Length Categories Using Form as the Reference Dimension

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
<th>Randomly Labelled, Aided Subjects</th>
<th>Randomly Labelled, Non-Rided Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
<td>Tie</td>
<td>Intermediate</td>
</tr>
<tr>
<td>Short</td>
<td>18</td>
<td>12</td>
<td>46</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Intermediate</td>
<td>6</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>5</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

2. Two procedural details need to be introduced at this time. First, the data tables given earlier in this method section are, in fact, the data based on the analysis of the data using the physical form as a judgment dimension. Second, to perform the chi square analyses which follow, the total number of data points in the model data was made equivalent to the number of data points for any group tested. Each model was represented by 200 data runs and therefore by 200 dominant run length counts. Each group of subjects had ten subjects each of whom contributed ten dominant run counts. Since the subject table had 100 counts associated with it, the 200 counts in the model table were divided by two when the distributions of dominant run categories were compared.
Table 22
Distribution of Dominant Run Length Categories
Using Labelling as the Reference Dimension

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td></td>
<td>81</td>
<td>9</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td>Tie</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

Randomly Labelled, Non-Aided Subjects

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Level run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td></td>
<td>90</td>
<td>5</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Tie</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

For comparisons sake, Table 23 shows the distribution of the same number of data points over these categories:

Table 23
Distribution of Dominant Run Length Categories for the Random Model

<table>
<thead>
<tr>
<th>Level run lengths</th>
<th>Short</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>86.5</td>
<td>4.5</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Tie</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>X</td>
</tr>
</tbody>
</table>

The Fisher Exact Test for RxC Contingency Tables was applied to the data. There were no significant differences between the random model category distribution and those of the subjects when the label judgment dimension was used. For the random vs. aided comparison, $p > 0.3948$ and for the random vs. nonaided comparison, $p > 0.567$. 
This allows us to infer that subjects did not use systematic strategies based on the labels on the data structures.

It is obvious by inspection that the choice patterns for the form judgment dimension are very different. This is verified by a chi square test which compared the random model data with subject data using the form judgment dimension. This showed that the category distribution using the form dimension was indeed different from random (p < .001). Therefore, it is inferred that if subjects are choosing to behave systematically, the systems used are related to the form rather than the label judgment dimension. This verifies that the second hypothesis, that subjects will tend to adopt strategies consistent with the physical format of the data structure even when the logical labelling is not in accord with the physical format, is correct.

Before testing the third and fourth hypotheses, a further procedural detail needs to be explained. In the earlier sections, the categorization scheme was used to compare the subject's behavior to that of the models. To test hypotheses 3 and 4, interest shifts from the identification of models to the subjects' tendencies to behave more or less systematically under the various experimental conditions. In order to assess this question, two further condensation procedures were applied to the data. First, the data from branch and level subject data were combined to produce overall exhaustive (branch + level) and sampling (branch + level) categories. Second, the cells not associated with model data were incorporated into these categories. In order to justify this
procedure, let us review the situation so far. Comparing the
subject data with Table 15 which displays the model names associated
with cells in the dominant run length category tables, it can be
noted that there is subject data in all but two cells of the table
while there only five of fifteen cells strongly associated with the
model data. The following rationale was used as a basis for
incorporating the data not associated with a model in the table into
the existing categories:

(a) exhaustive strategy: The branch exhaustive and level exhaustive
strategies respectively have only one cell associated with each
according to the models. However, the major feature of these two
models is that the behavior which they describe follows the rule
that the subject had most frequently chosen to make choices entirely
within a set before switching to a new set. From this point of
view, it does not matter if the pattern of choice within each set is
described by another, less "exhaustive" strategy. The criterion set
for the category "exhaustive run length" is a very stringent one and
is the more important determiner of behavior. Thus, all of the
cells in the row associated with the exhaustive branch run length
category and in the column associated with the exhaustive level run
length category were summed to produce the exhaustive total used in
testing hypotheses 3 and 4.

(b) sampling strategy: A similar grouping was applied to the
remaining unlabelled cells. The largest cell contents remaining
after the cells associated with random and exhaustive categories
have been assigned are those associated with the sampling models
(branch and level) in the model data. The major contentious group to be added to this group is the level tie run length category. In three of the four subject groups this cell is relatively small. In the fourth group (random labelled, aided), 12% of the data is in this cell. These data have been included as sampling rather than random data because, as was pointed out earlier, inspection of the actual subject choices producing this category, gave strong indication of systematic behavior.

Therefore, the subject data was recombined to form groups representing exhaustive, sampling and random categories in order to test hypotheses 3 and 4. The category assignment used is an expansion of the earlier table. It should be remembered that it is these broader categories which are used to test the last two hypotheses.

Table 24
Categories Used in Analysis of the Subject Data

<table>
<thead>
<tr>
<th>Branch run lengths</th>
<th>Short</th>
<th>Level run lengths</th>
<th>Tie</th>
<th>Intermediate</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>random</td>
<td>sampling</td>
<td>sampling</td>
<td>sampling</td>
<td>exhaustive</td>
</tr>
<tr>
<td>Tie</td>
<td>sampling</td>
<td>sampling</td>
<td>sampling</td>
<td>sampling</td>
<td>exhaustive</td>
</tr>
<tr>
<td>Intermediate</td>
<td>sampling</td>
<td>sampling</td>
<td>sampling</td>
<td>sampling</td>
<td>exhaustive</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>exhaustive</td>
<td>exhaustive</td>
<td>exhaustive</td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>

The third hypothesis stated that subjects presented with forms in which the usual physical format and logical labelling are in agreement will be more likely to adopt exhaustive search strategies than subjects for whom the labelling and format are not in
agreement. This hypothesis was tested by comparing the distribution of the random, sampling, and exhaustive categories across the combined groups which were systematically labelled with those which were randomly labelled.

The following table shows the distribution:

Table 25
Effects of Labelling on Search Systematicity

<table>
<thead>
<tr>
<th>Search Category</th>
<th>Labelling</th>
<th>Random</th>
<th>Sampling</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systematic</td>
<td>11</td>
<td>46</td>
<td>143</td>
<td>67</td>
</tr>
<tr>
<td>Random</td>
<td>21</td>
<td>112</td>
<td>67</td>
<td>67</td>
</tr>
</tbody>
</table>

A chi square statistic was calculated on these distributions. It showed that the distributions were significantly different (p < .001). Inspection of the table reveals that this difference is in the direction predicted in the hypothesis. There are fewer searches in the exhaustive category and more in the sampling and random categories for the randomly labelled condition. Thus, the third hypothesis has been supported.

Hypothesis 4 stated that aiding will enhance subjects' tendencies to search systematically. This hypothesis was tested by comparing the distribution of the random, sampling and exhaustive categories across the combined groups which were aided with those which were not aided.

The following table shows the distribution:
Table 26
Effects of Aiding on Search Systematicity

<table>
<thead>
<tr>
<th>Search Category</th>
<th>Aided</th>
<th>Not aided</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>25</td>
<td>7</td>
</tr>
<tr>
<td>Sampling</td>
<td>97</td>
<td>61</td>
</tr>
<tr>
<td>Exhaustive</td>
<td>78</td>
<td>132</td>
</tr>
</tbody>
</table>

A chi square statistic was calculated on these distributions. It showed that the distributions were significantly different (p < .001). Inspection of the table, however, reveals that this difference is in the opposite direction to that predicted in the hypothesis. There are fewer searches in the exhaustive category and more in the sampling and random categories for the aided condition. Thus, the fourth hypothesis must be rejected.

The third and fourth hypothesis tested the effects of the presence or absence of systematic labels and of aiding on the systematicity of the subjects' search behavior. A further question, however, concerns the interaction of the two experimental conditions. An inspection of the data in Table 27 suggests that the difference between the aided and not aided conditions is larger for the randomly labelled condition than for the systematically labelled condition.

Table 27
Effects of Aiding and Labelling on Search Systematicity

<table>
<thead>
<tr>
<th>Labels</th>
<th>Aiding</th>
<th>Random</th>
<th>Sampling</th>
<th>Exhaustive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systematic</td>
<td>Aided</td>
<td>7</td>
<td>29</td>
<td>64</td>
</tr>
<tr>
<td>Systematic</td>
<td>Not aided</td>
<td>4</td>
<td>17</td>
<td>79</td>
</tr>
<tr>
<td>Random</td>
<td>Aided</td>
<td>18</td>
<td>68</td>
<td>14</td>
</tr>
<tr>
<td>Random</td>
<td>Not aided</td>
<td>3</td>
<td>44</td>
<td>53</td>
</tr>
</tbody>
</table>
This suggestion was tested by assessing the partial associations for the three-way effect of aiding, labelling and search strategy using the BMDP data analysis package. This showed a significant ($p < .02$) effect for this interaction.
DISCUSSION

The discussion section will address first the results of this research and their implications and second, the methodology developed in the course of the research.

The Results and Their Implications

Choice strategies. The studies described in the literature review section show that people use structural features inherent in information in a wide variety of tasks. The results of this investigation show that in this situation, too, the strategies adopted most frequently are influenced by the structure of the information.

Statisticians would tell us that there is no statistical reason to search systematically under the constraints of the experiment. Subjects were told that the target was randomly chosen. However, the "intuitive statisticians" that served as subjects in this research did not behave in a way determined by the requirements of the task nor in accord with the trained statistician. Indeed, one subject revealed that he chose to search randomly because he had taken a number of statistics classes and knew that random search was as good as any other under the experimental conditions used. This was not typical.

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The average response in the category most strongly associated with random responding was only 8% of the total response. In contrast, 52.5% of the responses fell into the exhaustive search categories. This was the most frequently used response category and was also the strictest in terms of the systematic response required of the subjects. This demonstrates the strong tendencies of the human operator to adopt systems to pattern their responses irrespective of the formal demands of the problem domain.

It is important to note the failure of the a priori models to predict the complexity of the subjects' choice behavior. The models had stated, rather simplistically, that subjects would base their choices on one dimension (branch or level) of the tree. People's choice behavior was less single-minded. While many choice patterns were exhaustive along one dimension of the hierarchy, the same pattern contained some system based on the other dimension. For many choice sets, therefore, the question was not truly branch or level, but which one of branch or level predominated in controlling the systematic nature of the behavior.

An interesting feature of the data is the relative distribution of choices consistent with level rather than branch processing. Branch strategies correspond most closely to the depth-first type of memory search proposed by Collins and Quillian (1969) and discussed in the literature review section. The branch search strategy is also a model often used in simulations of problem solving, particularly of chess playing. Many chess playing programs (cf. Newell, Shaw & Simon, 1958) search down a branch for a prescribed span and then
move to other branches and proceed in a likewise manner. These patterns are most like the branch sampling strategy analyzed in this research. Branch sampling was chosen less than 8% of the time.

It is difficult to know how general a finding the relatively large preponderance of level strategies is. The hierarchy used in this research was broad but not deep. The impact of the pictorial representation of this broad, shallow hierarchy may have encouraged subjects to focus on the level dimension of the tree's structure rather then on the branch dimension. To adequately assess the relative preponderance of branch vs. level strategies, future research should use hierarchies varying in depth and breadth. Other research should also be done to determine the effect that the actual physical layout of the hierarchy had on the strategies adopted. To do this it would be necessary to vary the pictorial representation. By this I mean that stimuli used should include: (1) hierarchies in the horizontal orientation used in this research; (2) hierarchies arranged in a vertical orientation; and (3) hierarchies for which the branches are arranged in a circle about the parent node. This could further test the impact of physical vs. logical arrangement on dimension of choice.

If further study showed the preference for level strategies to be robust, it would have implications for information system design. The most frequently encountered, explicitly hierarchy used in computerized information systems are those which are often used in thesauri. In thesauri, the major forms of relationship are that between superordinates and subordinates (the so-called Broader Term
(BT) and Narrower Term (NT) relationship) and the Related Term (RT).

When thesauri are incorporated as user aids in online information systems, the BT-NT information is often thought to be the most important and useful. There is usually a great deal of effort put into the inclusion and display of BT-NT information. However, RT information often suffers by comparison and is often used as a "catch-all" category for both siblings of a concept and for related concepts occurring in diverse parts of the information structure. The results of the present study would suggest that thesaurus designers would do well to pay greater attention to developing the sibling (level) relationships for greater search efficacy.

Form vs. logical labels. The second hypothesis stated that subjects will tend to adopt strategies consistent with the physical format of the data structure (form) when the logical labelling is not in accord with the physical format. The data from those subjects for whom the effect of form and labels could be assessed separately (i.e., the randomly labelled groups) showed that the systems used were based predominantly on form rather than the logically defined labels. This was in line with the effects found in pattern learning studies by Jones (1976). Although subjects may learn about the logical form underlying data, the impact of the physical form of the data is great. This effect is further exemplified in the studies of the pictorial impact of hierarchical menu systems aids and training materials (Billingsley, 1982; Parton et al., 1985). The effect is, in fact, even suggested by Rouse (1978a). He says that "graphical display of a problem...can cause
the human to employ perceptual abilities" and earlier on the same page "precluding perceptual clues may force the use of thinking strategies" (p. 259). This underlines the importance of the pictorial impact effect.

**Labelling and systematicity.** The third hypothesis stated that subjects presented with forms in which the usual physical format and logical labelling are in agreement will be more likely to adopt exhaustive search strategies than subjects for whom the labelling and format are not in agreement.

The rationale behind this hypothesis was that subjects would "match" their behavior to the characteristics of the task environment. Therefore, subjects for whom the labels are systematically arranged would tend to behave more systematically and subjects for whom the labels were randomly arranged would tend to behave more randomly. Since there was no prior research to guide the form of this hypothesis, it is, of course possible that the hypothesis should have been that random labelling would produce more systematic behavior. The rationale for this converse hypothesis would be that subjects would respond to being placed in a more random situation by behaving more systematically to compensate for the increased confusion caused by the random labelling.

The data show that the original form of the hypothesis was supported. Subjects in the randomly labelled condition had a greater number of responses in the random and sampling categories.
than in the exhaustive category. Subjects in the systematically labelled group had more responses in the exhaustive search category.

Why was this so? The task is itself unstructured. It is not demanding. The random labelling suggests greater randomness in the task environment. Subjects respond to this by increased randomness in their behavior. This is substantiated by the significant interaction found between the effects of labelling and aiding. The data show that both features combined to enhance the overall tendency to behave less systematically in the randomly labelled aided condition. This would suggest that when subjects are freed from memory load by the presence of aiding, they are attempting to match their behavior to the task environment rather than to compensate for problems in the task environment. This effect might be likened to behavioral matching in social comparison theory.

Although this explanation may be the appropriate one, there is a possible confounding in the analysis. The analysis method used asked whether, overall, form or labels were used as a choice dimension by the subjects in the randomly labelled groups. It was shown that the subjects, in general, employed strategies which made it appear that the choices were made using form as a reference set. If the labels were used as a reference set, the data fit the random model. While the groups as a whole tended to follow the form dimension, there were one or two subjects who made comments which indicated that they had tried to use the labels as a choice dimension for one or more of the hierarchies they searched. Each time this was done, the analysis using the form reference set would
show 'random' search strategy. This may have contributed to increased randomness shown for the randomly labelled group. The extent to which this was done is difficult to determine.

Aiding. The fourth hypothesis stated that aiding will enhance subjects' tendencies to search systematically. This was based on Rouse's (1978a,b) work which studied fault diagnosis behavior in a graphically displayed network. Rouse's subjects had to locate nodes which caused failure in a numbered network. He found that aiding caused subjects to use more optimal solution paths, opposing this to 'brute force' strategies.

When this research was being planned, it seemed that the exhaustive strategies were the more systematic. Thus it was hypothesized that aiding increased the tendency to search systematically. The data presented in the present research showed that aiding decreased people's tendency to search exhaustively.

These results may have differed as a result of differences in the tasks studied. The demands on the information processing abilities of the subjects in the two studies were very different. Although Rouse's subjects worked in a smaller data structure (49 nodes vs. 75 in the present study), they were required to remember and integrate information about a number of different nodes in order to find a solution. The only requirement for the subjects in the present study was to keep on choosing nodes until a target was found. A more complex task should benefit more from aiding since in the more
complex task analytic rather than perceptual processing would be required for effective problem solving.

However, the original interpretation of Rouse's results may have been incorrect. The hypothesis was developed interpreting the optimal strategy as the more systematic in the Rouse studies and the exhaustive strategies as more systematic in the present study. But in some sense the 'brute force' strategy from Rouse had more surface similarity to the choices made using the exhaustive strategies. Both would have subjects choose some node and look systematically at the nodes surrounding the chosen node.

This suggests an area for future research. If the differences between the two studies are due to differences in the information processing load, a search task requiring information integration might cause subjects to move away from the more exhaustive search patterns to search sampling. If increased task demands did not cause the differences between the experiments, the shift in search patterns would not occur.

The Method

A major contribution of this research has been in the development of a method for identifying a quantitative indicator for search strategies. Prior studies of information search used two main measures, response time and errors. Studies of human memory have used response time and output analysis (e.g., chunking) to imply search strategy. These measures are indirect indicators of
strategies at best. At worst, they may be confounded by factors related to other characteristics of the information processing and decision making systems. This method takes as data the choices which reflect the strategies studied.

The decision to study the search strategy directly contributed the greatest challenge to this research project. We needed something to count. Our initial plan had been to use a known technique such as Markov chaining to define search strategies. However, on close examination, a key assumption of these models came to light. If Markov and other stochastic models are to work, it is necessary that the probabilities attached to paths leaving and coming to a node are constant. However, the search strategies studied here are essentially dynamic. The probabilities change as a function of the number of times other nodes related to that node have been chosen. Thus stochastic modelling was inappropriate.

The transitions analysis method suggested by Payne (1976) had advantages. It gave us something to count. Transition types were not a particularly intuitive metric in the task but they did produce differences between the categories which were related to the search strategies studied. Unfortunately, the category indicators which were not sufficiently precise to differentiate search strategies.

Another type of analysis, discriminant analysis, could have been applied to the choice data. Discriminant analysis proceeds by looking first at the models. For each model, it produces a set of
probabilities associated with any change of state. For example, it
determines the probability of choosing a particular branch, then of
choosing one node in the branch, then of choosing one node given
that one has already chosen one node, and so on. These
probabilities are then applied node by node to the thirty choice
patterns for each subject. The combined likelihood of each set of
choices is compared to that of the models and the nearest one is
chosen as the strategy exhibited by the 30 choice sequence. This
form of analysis would have been overly specific. It would have
evaluated how close the subject data fit to very precisely defined
models. If there were variation (for example, the variation seen in
the exhaustive strategies in which the second dimension was used in
determination of the search protocol) the model would not have given
us any insight into the determinants of choice. By focusing on
specific detail, we would have missed general and important
characteristics of the data.

A method of analysis was needed which was fine enough to distinguish
the models but coarse enough to allow us to ignore variations in the
data which were not themselves of interest to the present
investigation and which would at the same time not hide variations
which were. The dominant run length categorization method did help
to reveal important distinctions among the models while glossing
over distinctions which did not contribute to our understanding of
the data.

The dominant run length method is not perfect. Some data points
have been misclassified. For example, at least one subject chose
data points from the first and second levels of the hierarchy alternately. In the analysis, this comes out to be a dominant run of the "short run length" category along the level dimension. Clearly, however, the subject utilized level information in making his choices. The choices were not simply random along this dimension. The method is also not informative about complex patterns of choice in the data. Many subjects made choices which could be described verbally and which were clearly related to the physical structure of the hierarchy. For example, subjects might choose a symmetrical pattern like \{A1,1; A1; A1,4; A2,1; A2; A2,4;\ldots\} or similar variations, the pattern of which was not captured by the present methodology. Neither this method nor any other currently available method that I have been able to identify can provide a quantitative metric for these patterns.

The dominant run length method not only permitted the analysis of search strategies in this research but provided a method that could be extended to other data structures and other models. Any structure which could be described in terms of sets and supersets can be analyzed in this way. The method could be extended to network structures, in general, or to the examination of the role of set size as a determinant of strategic choice. The method could be used with networks and hierarchies for which the nodes correspond to well and ill known concepts to investigate the relationship between search and knowledge structures. It could serve as a valuable tool for future research.
SUMMARY AND CONCLUSIONS

This research investigated the way an abstract data structure, the hierarchy, influenced the methods people used in looking for a target embedded in that structure. The search patterns found are referred to as search strategies. The search strategies proposed were formalized into search models which were described in terms of their relationship to the physical features—branch and level—of the hierarchy and in terms of how systematic they were. Five search models were proposed: random, branch exhaustive, branch sampling, level exhaustive and level sampling.

A methodology was developed for identifying choice patterns characteristic of the search models. This methodology used uninterrupted sequences of consecutive choices ("runs") as the underlying measurement unit.

The choice patterns of forty subjects were compared to those of the models. Subjects were given the task of finding random targets. However, their behavior was seldom categorized as random. Many choice sequences were most strongly influenced by the level dimension of the hierarchy. An interesting feature of the data was the tendency to-use both level and branch dimensions to structure the strategies adopted.

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Half of the subjects were given data structures for which the logical labels were randomly reassigned to the nodes. These subjects tended to use the physical arrangement of the hierarchy as a basis for systematic searching rather than the logical labelling. Using data structures that were logically labelled did affect search behavior differently from using data structures for which the logical labels were randomly rearranged. Systematically labelled data structures tended to produce behavior which was more systematic (a larger number of choice sequences characterized as exhaustive vs. sampling or random) than that produced by randomly labelled data structures.

Half of the subjects in the systematically labelled and half of the subjects in the randomly labelled groups were asked to cross off nodes as they had chosen them. This effect was referred to as aiding since it permitted the subject to exclude previously chosen nodes from their choice set without reliance upon their memory for previous choices. It was shown that subjects who were not given aiding were more systematic (had a larger number of choices in the exhaustive category) than those who were aided.

This research determined that it is possible to find a methodology for describing search strategies characteristic of people looking for information in an hierarchical data structure. In addition, it has demonstrated that these strategies are related to the physical attributes of the data structure and that they can be influenced by the form of labelling used and the provision of memory aids.
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APPENDIX A

THE SEARCH MODELS
Part 1:

Verbal Descriptions of the Search Models

Model 1: Random search

This model assumes that the physical and logical arrangement of the data does not affect search. This random search model assumes that the probability of moving from a node to any other node in the structure is calculated by $1/N-1$ where $N$ = the number of nodes not chosen by that time.

Model 2: Level exhaustive search

This model assumes that the subject searches every node at every level of the tree and that every node at a chosen level is searched before the searcher moves to the next level. Therefore, the probabilities associated with moving to a given level are a function of the number of levels, the number of nodes at a given level (depth) and of the number of nodes at that level already chosen.

Model 3: Level sampling search

This model assumes that the subject moves from level to level as suggested in the previous model but that the subject terminates his search within each level before all of the nodes at a given level have been chosen. It is further assumed that a subject will sample some fixed number of nodes at the chosen level before moving to the next level. The likelihood that a subject will choose to sample from some level different from the level chosen increases as a function of the number of items at that level which have already been chosen.

Model 4: Branch exhaustive search

This model assumes that the subject moves from the parent node through the tree and exhaustively searches all the sons and grandchildren of a given parent before moving to a second branch and exhaustively searching it. The probabilities of accessing each node therefore are a function of the number of the number of descendents at each branch of the tree. This model is distinguished by the characteristic that all the children of a given node will be searched before a second branch of the tree is accessed.
Model 5: Branch sampling search

This model assumes that the subject moves from branch to branch as suggested in the previous model but that the subject terminates his search within each branch before all of the nodes in a given branch have been chosen. The likelihood that a subject will choose to sample from some branch different from the branch chosen increases as a function of the number of items in that branch which have already been chosen.
Part 2
Algorithms for the Search Models

Model 1: Random search

Definitions:
Let the number of nodes available in the structure = N.

Algorithm:
0. Let the subject choose a node
1. If this is the correct node, stop; else,
2. $N = N - 1$
3. If $N > 0$, the probability of choosing any particular node = $\frac{1}{N}$; go to 0
4. If $N = 0$, end search.

Model 2: Level exhaustive search

Definitions:
The level ($L/d_{i/u}$) of a given node is determined by counting the number of nodes between the node and the root of the tree, including the node of the tree in the count.

All the nodes which are of the same distance are defined as of the same level.

Let the number of nodes of an equivalent level = $n$.

Let $n_{\text{max}}$ = the original value of $n$ for each level.

Let the number of nodes in the tree = N.

Algorithm:
0. Let the subject choose a node $X$ at Level $L$.
1. If $X$ is the correct node, stop; else continue
2. $n = n - 1$
3. If \( n > 0 \), the probability of choosing another node at this level = 1
   the probability of choosing any given node at this level = \( \frac{1}{n} \);
goto 2

4. If \( n < 0 \), \( N = N - n \)
   \( \max \)

5. If \( N > 0 \), go to 0; If \( N < 0 \), stop.

**Model 3: Level sampling search**

Definitions:

In addition to the definitions characteristic of the level exhaustive search, add the following:

Let \( m = \) the number of nodes at a given level chosen at any given point in the search. Initially, \( m = 0 \).

Algorithm:

0. Let the subject choose a node \( X \) at level \( L \).
   \( i \quad j \)
1. If this is the correct node, stop; else, continue

2. \( m = m + 1; \quad n = n - 1; \)

3. If \( n > 0 \), the probability of choosing another node at this level = 1 until two nodes have been chosen; after that the probability = \( \frac{1}{m} \); if \( (1 - \frac{1}{m}) > \frac{1}{m} \) go to 2;
   else go to 4;

4. \( N = N - n; \)

5. If \( N > 0 \), go to 0; if \( N < 0 \), stop.

**Model 4: Branch exhaustive search**

Definitions:

A branch is defined as a set whose members include those nodes whose paths enter nodes at a higher level through a single common parent.

Let the number of nodes within a branch = \( n \).

Let \( n \ max \) = the original i.e. maximum value of \( n \).

Let the total number of nodes in the tree = \( N \).
Algorithm:

0. Let the subject choose a node $X$ at Branch $B_i$.

1. If $X$ is the correct node, stop; else continue

2. $n = n - 1$

3. If $n > 0$, the probability of choosing another node in this branch = $1$. The probability of choosing any given node in this branch = $1/n$; go to 2

4. If $n < 0$, $N = N - n$

Model 5: Branch sampling search

Definitions:
In addition to the definitions given for the branch exhaustive search, add the following:

Let $m =$ the number of nodes within a branch which have already been accessed at any given point in the search. Initially, $m = 0$.

Algorithm:

0. Let the subject choose a node $X$ at Branch $B_i$.

1. If this is the correct node, stop; else, continue

2. $m = m + 1$; $n = n - 1$

3. If $n > 0$, the probability of choosing another node in this branch = $1$ until two nodes have been chosen; after that the probability = $1/m$; if $(1 - 1/m) > 1/m$ go to 2; else go to 4;

4. $N = N - n$

5. If $N > 0$, go to 0; if $N < 0$, stop.
Part 3

Programs for Generating Search Models
Random Model

C RANDOM MODEL
REAL *8 ARRAY(115),INPUT(115),BLANKS
DATA BLANKS /' ' /
WRITE(8,2)
2 FORMAT(1H , 'RANDOM MODEL PROGRAM')
READ(4,1) NN
READ(4,1) NREP
1 FORMAT(I3)
C READ DATA INTO INPUT ARRAY
DO 5 I=1,NN
5 READ(4,22) INPUT(I)
DO 50 J=1,NREP
IX=533+(J*50)
WRITE(8,12) J
12 FORMAT(1', THIS IS RUN NO. ',I3)
C FILL ARRAY WITH BLANKS
DO 3 I=1,NN
3 ARRAY(I)=BLANKS
C MOVE INPUT INTO ARRAY RANDOMLY
DO 10 I=1,NN
7 CALL IRANU(IX,0,NN,IY)
IF(ARRAY(IY).NE.BLANKS) GO TO 7
ARRAY(IY)=INPUT(I)
10 CONTINUE
C PRINT OUT 30 NODES OF RANDOMIZED ARRAY
WRITE(8,42) (ARRAY(I),I=1,30)
50 CONTINUE
22 FORMAT(A5)
42 FORMAT(IX,A5,56X)
STOP
END
Sampling Models Program

C SAMPLING MODELS PROGRAM—SAMPLE TWO
WRITE(6,1)
1 FORMAT(1H,'SAMPLING GENERATION PROGRAM')

C DECLARATIONS
INTEGER CTR
INTEGER S
REAL*8 ARRAY(15,60)
DIMENSION NSET(15)
REAL*8 BLANKS
DATA BLANKS/' '/
REAL*8 RNDARA(15,60)
INTEGER PTR(IB)

C READ MODEL PARAMETERS
READ(4,3) S
READ(4,3) NN
3 FORMAT(I3)

C DETERMINE THE NUMBER OF NODES IN EACH SET
DO 10 1=1,S
READ(4,3) NSET(I)
10 CONTINUE

C READ DATA INTO INPUT ARRAY
DO 12 1=1,S
K=NSET(I)
DO 12 J=1,K
12 READ(4,5) ARRAY(I,J)
5 FORMAT(A5)
IX=737+(K*54)

C REPEAT THE CYCLE
DO 200 K=1,200
WRITE(8,21) K
21 FORMAT(1H,'THIS IS RUN NO. ',I3)

C READ DATA INTO RANDOMIZED ARRAY
C CLEAR RNDARA
DO 16 I=1,S
L=NSET(I)
DO 16 J=1,L
16 RNDARA(I,J)=BLANKS

C MOVE DATA INTO RNDARA
DO 22 I=1,S
L=NSET(I)
DO 22 J=1,L
20 CALL IRANU(IX,1,L,IY)
IF(RNDARA(I,IY).NE.BLANKS) GO TO 20
RNDARA(I,IY)=ARRAY(I,J)
22 CONTINUE
C OUTPUT NODES IN MODEL-DETERMINED ORDER
C INITIALIZE SET POINTERS(PTR)
   DO 26 I=1,S
26   PTR(I)=1
C N=NO. OF NODES CHOSEN
   N=0
C BEGIN COUNT
   N=N+1
   IF(N.GT.30) GO TO 200
C CHOOSE A SET TO SAMPLE FROM
   CALL IRANU(IX,1,S,IY)
C DETERMINE IF ALL MEMBERS OF THE SET HAVE BEEN CHOSEN
   IN=IY
C BEGIN COUNT OF NO. OF NODES IN SET CHOSEN(IN)
   IF(PTR(IN).GT.NSET(IN)) GO TO 34
C OUTPUT FIRST TWO MEMBERS OF SET IF AVAILABLE
   CTR=1
38   M=PTR(IN)
   WRITE(8,101) RNDARA(IN,M)
101  FORMAT(1X,A5)
   CTR=CTR+1
   PTR(IN)=PTR(IN)+1
   N=N+1
   IF(N.GT.30) GO TO 200
   IF(PTR(IN).GT.NSET(IN)) GO TO 34
   IF(CTR.LE.2) GO TO 38
   C CALCULATE PROBABILITIES OF STAYING IN SET VS. SWITCHING
   C IN GENERAL P(STAYING)=1/NO. OF NODES CHOSEN -1
   LMT=CTR-1
46   CALL IRANU(IX,1,LMT,IY)
   IF(IY.LE.1) GO TO 38
   IF(IY.GT.1) GO TO 34
200 CONTINUE
   STOP
END
Exhaustive Models Program

C EXHAUSTIVE MODELS PROGRAM
WRITE(8,1)
1 FORMAT(1H,'EXHAUSTIVE MODELS PROGRAM')
C DECLARATIONS
INTEGER CTR
INTEGER S
REAL*8 ARRAY(15,50)
DIMENSION NSET(15)
REAL*8 BLANKS
DATA BLANKS/' '/
REAL*8 RNDARA(15,60)
INTEGER PTR(15)
C READ MODEL PARAMETERS
READ(4,3) S
READ(4,3) NN
3 FORMAT(I3)
C DETERMINE THE NUMBER OF NODES IN EACH SET
DO 10 I=1,S
  READ(4,3) NSET(I)
10 CONTINUE
C READ DATA INTO INPUT ARRAY
DO 12 I=1,S
  K=NSET(I)
  DO 12 J=1,K
     READ(4,5) ARRAY(I,J)
12  FORMAT(A5)
  IX=357+(K*54)
C REPEAT THE CYCLE
DO 200 K=1,200
  WRITE(8,21) K
21 FORMAT(1H,'THIS IS RUN NO. ',I3)
C ENTER DATA INTO RANDOMIZED ARRAY
C CLEAR RNDARA
DO 16 I=1,S
  L=NSET(I)
  DO 16 J=1,L
16   RNDARA(I,J)=BLANKS
C MOVE DATA INTO RNDARA
DO 22 I=1,S
  L=NSET(I)
  DO 22 J=1,L
20   CALL IRANU(IX,1,L,IY)
   IF(RNDARA(I,IY).NE.BLANKS) GO TO 20
   RNDARA(I,IY)=ARRAY(I,J)
C CONTINUE
C OUTPUT NODES IN MODEL-DETERMINED ORDER
C INITIALIZE SET POINTERS(PTR)
   DO 26 I=1,S
   PTR(I)=1
C N=NO. OF NODES CHOSEN
   N=0
C BEGIN COUNT
   N=N+1
34   IF(N.GT.30) GO TO 200
C CHOOSE A SET TO SAMPLE FROM
   CALL IRANU(IX,1,S,IY)
C DETERMINE IF ALL MEMBERS OF THE SET HAVE BEEN CHOSEN
   IN=IY
C BEGIN COUNT OF NO. OF NODES IN SET CHOSEN(IN)
   IF(PTR(IN).GT.NSET(IN)) GO TO 34
C OUTPUT ALL MEMBERS OF SET CHOSEN
38   M=PTR(IN)
   WRITE(6,101) RNDARA(IN,M)
101  FORMAT(1X,A5,66X)
   PTR(IN)=PTR(IN)+1
   N=N+1
   IF(N.GT.30) GO TO 200
   IF(PTR(IN).LE.NSET(IN)) GO TO 38
   IF(PTR(IN).GT.NSET(IN)) GO TO 34
200 CONTINUE
STOP
END
APPENDIX B

DATA ANALYSIS PROGRAMS
Transitions Analysis Program

C DATA ANALYSIS PROGRAM
C SYSTEMATICALLY ARRANGED DATA
WRITE(6,1)
  1 FORMAT(IH , 'DATA ANALYSIS')
C DECLARATIONS
REAL*8 DATA1,DATA2,MSG
REAL*8 LEVEL(2,60)
DIMENSION NBRNCH(20)
DIMENSION NLEVEL(5)
INTEGER LIBJ,LIBNJ,LNIBJ,LNIBNJ
INTEGER B1,B2,L1,L2,WBR,WLVL,NREP
C SET UP COMPARISONS
READ(4,3) NBR
READ(4,3) NREP
READ(4,3) NLVL
READ(4,3) NTRANS
  3 FORMAT(I3)
C DETERMINE NO. OF NODES PER SET
  DO 10 I=1,NBR

10 READ(4,3) NBRNCH(I)
  DO 12 I=1,NLVL

12 READ(4,3) NLEVEL(I)
C READ DATA INTO SETS
  DO 16 I=1,NBR

16 READ(4,13) BRNCH(I,J)
  DO 16 J=1,K

13 FORMAT(A5)

20 READ(4,13) LEVEL(I,J)
C COMPLETE COUUNT FOR NREP SETS OF DATA
READ(3,221) MSG
WRITE(6,121) MSG
  121 FORMAT(IH ,A8)

221 FORMAT(A8)

DO 400 L=1,NREP
LIBJ=0
LIBNJ=0
LNIBJ=0
LNIBNJ=0
WBR=0
WLVL=0
WRITE(5,41) L
41 FORMAT(1H , 'STATISTICS FROM HIERARCHY NUMBER ',I3)  
C READ FIRST ITEM OF OUTPUT DATASET
READ(3,23) DATA1  
DO 100 N=1,NTRANS  
C PROCEED THROUGH DATASET
DATA2=DATA1  
READ(3,23) DATA1  
23 FORMAT(1X,A5)  
WRITE(6,27) DATA1,DATA2  
27 FORMAT(1H , 'DATA1=',A5,' DATA2=',A5)  
C DO BRANCH COMPARISONS
DO 32 I=1,NBR  
K=NBRNCH(I)  
DO 32 J=1,K  
IF(DATA1.EQ.BRNCH(I,J)) B1=I  
IF(DATA2.EQ.BRNCH(I,J)) B2=I  
32 CONTINUE  
C DO LEVEL COMPARISONS
DO 42 I=1,NLVL  
K=NLEVEL(I)  
DO 42 J=1,K  
IF(DATA1.EQ.LEVEL(I,J)) L1=I  
IF(DATA2.EQ.LEVEL(I,J)) L2=I  
42 CONTINUE  
C DO TRANSITION TYPE CALCULATIONS
IF((L1.EQ.L2).AND.(B1.EQ.B2)) LIBJ=LIBJ+1  
IF((L1.EQ.L2).AND.(B1.NE.B2)) LIBNJ=LIBNJ+1  
IF((L1.NE.L2).AND.(B1.EQ.B2)) LNIBJ=LNIBJ+1  
IF((L1.NE.L2).AND.(B1.NE.B2)) LNIBNJ=LNIBNJ+1  
WRITE(6,37) N,LIBJ,LIBNJ,LIBJ,LIBNJ  
37 FORMAT(1H , 'N=',I3,' LIBJ=',I3,' LIBNJ=',I3,  
       ' LNIBJ=',I3,' LNIBNJ=',I3)  
100 CONTINUE  
WBR=LIBJ + LNIBJ  
WLVL= LIBJ + LIBNJ  
WRITE(6,39) WBR,WLVL  
39 FORMAT(1H , 'WBR=',I3,' WLVL=',I3)  
400 CONTINUE  
STOP  
END
Runs Analysis Program:
Systematically Labelled Data

C RUNS ANALYSIS PROGRAM
C SUBJECT DATA
C DECLARATIONS
REAL*8 DATA1, DATA2, MSG
REAL*8 BRNCH(15, 5)
REAL*8 LEVEL(2, 60)
INTEGER RUNCT, CTR
DIMENSION NBRNCH(20)
DIMENSION NLEVEL(5)
INTEGER BRRUN(10, 5), L1RUN(10, 15), L2RUN(10, 30)
INTEGER B1, B2, L1, L2, WBR, WLVL, NREP
INTEGER BRTOT(5), L1TOT(15), L2TOT(30)
REAL*8 USESET(30)
WRITE(8, 1)
1 FORMAT(1H, 'RUNS ANALYSIS')
C SET UP COMPARISONS
READ(4, 3) NBR
READ(4, 3) NLVL
READ(4, 3) NTRANS
3 FORMAT(13)
C DETERMINE NO. OF NODES PER SET
DO 10 I=1, NBR
10 READ(4, 3) NBRNCH(I)
DO 12 I=1, NLVL
12 READ(4, 3) NLEVEL(I)
C READ DATA INTO SETS
DO 16 I=1, NBR
K=NBRNCH(I)
DO 16 J=1, K
16 READ(4, 13) BRNCH(I, J)
13 FORMAT(AS)
DO 20 I=1, NLVL
K=NLEVEL(I)
DO 20 J=1, K
20 READ(4, 13) LEVEL(I, J)
READ(3, 221) MSG
WRITE(8, 121) MSG
121 FORMAT(1H, A12)
221 FORMAT(1H, A12)
C SET UP COUNTERS
DO 110 J=1, 5
BRTOT(J)=0
DO 110 I=1,10
BRRUN(I,J)=0
110 CONTINUE
DO 120 J=1,15
L1TOT(J)=0
DO 120 I=1,10
L1RUN(I,J)=0
120 CONTINUE
DO 130 J=1,30
L2TOT(J)=0
DO 130 I=1,10
L2RUN(I,J)=0
130 CONTINUE
C COMPLETE TEN REPETITIONS
DO 400 L=1,10
C COPY DATASET TO USESET
DO 40 I=1,30
READ(3,23) DATAI
23 FORMAT(A5)
USESET(I)=DATAI
40 CONTINUE
C DO BRANCH COMPARISONS
RUNCT=1
CTR=1
52 IF(CTR.GT.NTRANS) GO TO 200
DO 32 I=1,NBR
M=CTR+1
K=NBRNCH(I)
DO 32 J=1,K
IF(USESET(CTR).EQ.BRNCH(I,J)) B1=I
IF(USESET(M).EQ.BRNCH(I,J)) B2=I
32 CONTINUE
IF(B1.EQ.B2) RUNCT=RUNCT+1
CTR=CTR+1
IF(B1.EQ.B2) GO TO 52
C IF RUN IS TERMINATED
150 BRRUN(L,RUNCT)=BRRUN(L,RUNCT)+1
RUNCT=1
IF(CTR.LE.NTRANS) GO TO 52
200 IF(B1.EQ.B2) BRRUN(L,RUNCT)=BRRUN(L,RUNCT)+1
IF(B1.NE.B2) BRRUN(L,1)=BRRUN(L,1)+1
C DO LEVEL COMPARISONS
RUNCT=1
CTR=1
62 IF(CTR.GT.NTRANS) GO TO 300
DO 42 I=1,MLVL
M=CTR+1
K=NLEVEL(I)
DO 42 J=1,K
IF(USESET(CTR).EQ.LEVEL(I,J)) B1=I
IF(USESET(M).EQ.LEVEL(I,J)) B2=I
42 CONTINUE
IF(B1.EQ.B2) RUNCT=RUNCT+1
CTR = CTR + 1
IF (B1.EQ. B2) GO TO 62

C IF RUN IS TERMINATED
IF (B1.EQ. 1) L1RUN(L, RUNCT) = L1RUN(L, RUNCT) + 1
IF (B1.EQ. 2) L2RUN(L, RUNCT) = L2RUN(L, RUNCT) + 1
RUNCT = 1
GO TO 62

300 IF ((B1.EQ. B2).AND. (B1.EQ. 1))
* L1RUN(L, RUNCT) = L1RUN(L, RUNCT) + 1
IF ((B1.EQ. B2).AND. (B1.EQ. 2))
* L2RUN(L, RUNCT) = L2RUN(L, RUNCT) + 1
IF ((B1.NE. B2).AND. (B2.EQ. 1))
* L1RUN(L, RUNCT) = L1RUN(L, RUNCT) + 1
IF ((B1.NE. B2).AND. (B2.EQ. 2))
* L2RUN(L, RUNCT) = L2RUN(L, RUNCT) + 1

400 CONTINUE

C DO TOTALS OVER RUN LENGTHS
DO 26 J = 1, 5
   DO 26 I = 1, 10
26    BRTOT(J) = BRTOT(J) + BRRUN(I, J)
DO 36 J = 1, 15
   DO 36 I = 1, 10
36    L1TOT(J) = L1TOT(J) + L1RUN(I, J)
DO 46 J = 1, 30
   DO 46 I = 1, 10
46    L2TOT(J) = L2TOT(J) + L2RUN(I, J)

C WRITE RESULTS TO DATASET
C WRITE BRANCH DATA
WRITE (8, 27)
27 FORMAT (1H , 'BRANCH RUNS', '53X', 'TOTAL')
   DO 44 J = 1, 5
44    WRITE (8, 37) J, (BRRUN(I, J), I = 1, 10), BRTOT(J)
37 FORMAT (1H , '7X', '12', 5X, 10(3X, 12), 3X, 13)

C WRITE LEVEL DATA
WRITE (8, 47)
WRITE (8, 49)
47 FORMAT (1H , 'LEVEL RUNS')
49 FORMAT (1H , 'LEVEL ONE RUNS')
   DO 64 J = 1, 15
64    WRITE (8, 57) J, (L1RUN(I, J), I = 1, 10), L1TOT(J)
WRITE (8, 57)
57 FORMAT (1H , 'LEVEL TWO RUNS')
   DO 66 J = 1, 30
66    WRITE (8, 37) J, (L2RUN(I, J), I = 1, 10), L2TOT(J)
STOP
END
Runs Analysis Program:
Randomly Labelled Data

C RUNS ANALYSIS PROGRAM
C USES RANDOM PARAMETER SET (FOLLOWS FORM)
C SUBJECT DATA
C DECLARATIONS

REAL's DATA1, DATA2, MSG
REAL's BRNCH(15,5)
REAL's LEVEL(2,60)
INTEGER RUNCT, CTR
DIMENSION NBRNCH(20)
DIMENSION NLEVEL(5)
INTEGER BRRUN(10,5), L1RUN(10,15), L2RUN(10,30)
INTEGER B1, B2, L1, L2, WBR, WLVL, NREP
INTEGER BRTOT(5), L1TOT(15), L2TOT(30)
REAL's USESET(30)
WRITE(S, l)
1 FORMAT(i1, 'RUNS ANALYSIS—FOLLOWS FORM NOT LABELS')
READ(3, 221) MSG
WRITE(S, 121) MSG
C SET UP COMPARISONS
READ(4, 3) NBR
READ(4, 3) NLVL
READ(4, 3) NTRANS
3 FORMAT(i3)
C DETERMINE NO. OF NODES PER SET
DO 10 I = 1, NBR
10 READ(4, 3) NBRNCH(I)
DO 12 I = 1, NLVL
12 READ(4, 3) NLEVEL(I)
C SET UP COUNTERS
DO 110 J = 1, 5
BRTOT(J) = 0
DO 110 I = 1, 10
BRRUN(I, J) = 0
110 CONTINUE
DO 120 J = 1, 15
L1TOT(J) = 0
DO 120 I = 1, 10
L1RUN(I, J) = 0
120 CONTINUE
DO 130 J = 1, 30
L2TOT(J) = 0
DO 130 I = 1, 10
L2RUN(I,J)=0
130 CONTINUE
C COMPLETE TEN REPETITIONS
   DO 400 L=1,10
   C READ PARAMETER DATA INTO SETS
C DO 16 I=1,NBR
   K=NBRNCH(I)
   DO 16 J=1,K
   16 READ(4,13) BRNCH(I,J)
C FORMAT(A5)
   DO 20 I=1,NLVL
   K=NLLEVEL(I)
   DO 20 J=1,K
   20 READ(4,13) LEVEL(I,J)
   121 FORMAT(dH,A12)
   221 FORMAT(dH,A12)
C COPY SUBJECT DATA TO USESET
C DO 40 1=1,30
   READ(3,23) DATA1
   23 FORMAT(A5)
   USESET(I)=DATA1
40 CONTINUE
C DO BRANCH COMPARISONS
   RUNCT=1
   CTR=1
   52 IF(CTR.GT.NTRANS) GO TO 200
   DO 32 I=1,NBR
   K=CTR+1
   DO 32 J=1,K
   IF (USESET(CTR).EQ.BRNCH(I,J)) B1=I
   IF (USESET(M).EQ.BRNCH(I,J)) B2=I
32 CONTINUE
   IF(B1.EQ.B2) RUNCT=RUNCT+1
   CTR=CTR+1
   IF(B1.EQ.B2) GO TO 52
C IF RUN IS TERMINATED
C DO 150 L=1,10
150 BRRUN(L,RUNCT)=BRRUN(L,RUNCT)+1
   RUNCT=1
   IF(CTR.LE.NTRANS) GO TO 52
200 IF(B1.EQ.B2) BRRUN(L,RUNCT)=BRRUN(L,RUNCT)+1
   IF(B1.NE.B2) BRRUN(L,1)=BRRUN(L,1)+1
C DO LEVEL COMPARISONS
   RUNCT=1
   CTR=1
   62 IF(CTR.GT.NTRANS) GO TO 300
   DO 42 I=1,NLVL
   K=CTR+1
   DO 42 J=1,K
   IF (USESET(CTR).EQ.LEVEL(I,J)) B1=I
   IF (USESET(M).EQ.LEVEL(I,J)) B2=I
42 CONTINUE
IF (B1.EQ.B2) RUNCT=RUNCT+1
CTR=CTR+1
IF (B1.EQ.B2) GO TO 62
C IF RUN IS TERMINATED
IF (B1.EQ.1) LIRUN(L, RUNCT)=LIRUN(L, RUNCT)+1
IF (B1.EQ.2) L2RUN(L, RUNCT)=L2RUN(L, RUNCT)+1
RUNCT=1
GO TO 62
300 IF ((B1.EQ.B2).AND.(B1.EQ.1))
   * LIRUN(L, RUNCT)=LIRUN(L, RUNCT)+1
   IF((B1.EQ.B2).AND.(B1.EQ.2))
   * L2RUN(L, RUNCT)=L2RUN(L, RUNCT)+1
   IF((B1.NE.B2).AND.(B2.EQ.1))
   * LIRUN(L, RUNCT)=LIRUN(L, RUNCT)+1
   IF((B1.NE.B2).AND.(B2.EQ.2))
   * L2RUN(L, RUNCT)=L2RUN(L, RUNCT)+1
400 CONTINUE
C DO TOTALS OVER RUN LENGTHS
   DO 26 J=1, 5
   DO 26 I=1, 10
26 BRTOT(J)=BRTOT(J)+BRRUN(I, J)
   DO 36 J=1, 15
   DO 36 I=1, 10
36 L1TOT(J)=L1TOT(J)+L1RUN(I, J)
   DO 46 J=1, 30
   DO 46 I=1, 10
46 L2TOT(J)=L2TOT(J)+L2RUN(I, J)
C WRITE RESULTS TO DATASET
C WRITE BRANCH DATA
WRITE(8, 27)
   FORMAT(1H , 'BRANCH RUNS ', 53X, 'TOTAL')
   DO 44 J=1, 5
44 WRITE(8, 37) J, (BRRUN(I, J), I=1, 10), BRTOT(J)
   FORMAT(1H , 7X, 12, 5X, 10(3X, 12), 3X, 13)
C WRITE LEVEL DATA
WRITE(8, 47)
   FORMAT(1H , 'LEVEL RUNS')
49 FORMAT(1H , 'LEVEL ONE RUNS')
   DO 64 J=1, 15
64 WRITE(8, 57) J, (L1RUN(I, J), I=1, 10), L1TOT(J)
WRITE(8, 57)
   FORMAT(1H , 'LEVEL TWO RUNS')
   DO 66 J=1, 30
66 WRITE(8, 57) J, (L2RUN(I, J), I=1, 10), L2TOT(J)
STOP
END