AD-A171 068 COGNITIVE EFFORT AND DECISION MAKING STRATEGIES: A COMPONENTIAL ANALYSIS OF CHOICE(U) DUKE UNIV DURHAM NC J R BETTMAN ET AL. 31 JUL 86 RR-86-2 N00014-80-C-0114 1/1

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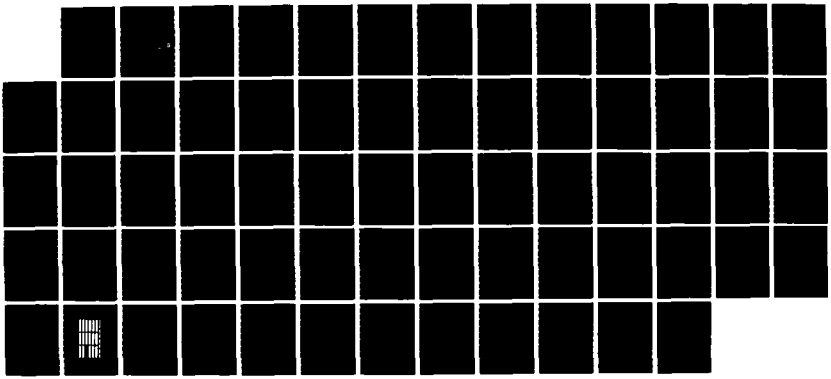

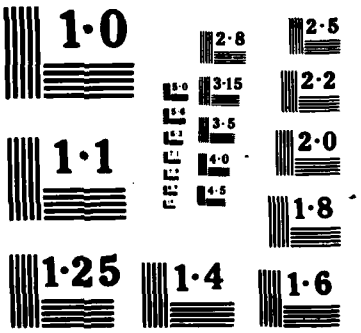
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ONR CONTRACT NUMBER: N00014-80-C-0114
WORK UNIT NUMBER: R & T 4425063

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AD-A171 068

COGNITIVE EFFORT AND DECISION MAKING STRATEGIES: A COMPONENTIAL ANALYSIS OF CHOICE

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: 86-2

2. GOVT ACCESSION NO.: AD-A171 068

3. RECIPIENT'S CATALOG NUMBER:

4. TITLE (and Subtitle): COGNITIVE EFFORT AND DECISION MAKING STRATEGIES: A COMPONENTIAL ANALYSIS OF CHOICE

5. TYPE OF REPORT & PERIOD COVERED: Research

6. PERFORMING ORG. REPORT NUMBER:

7. AUTHOR(s):
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8. CONTRACT OR GRANT NUMBER(s): N00014-80-C-0114

9. PERFORMING ORGANIZATION NAME AND ADDRESS: Duke University

10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: RT 4425063

11. CONTROLLING OFFICE NAME AND ADDRESS: ONR, Arlington, VA 22217-5000

12. REPORT DATE: July 31, 1986

13. NUMBER OF PAGES: 55

14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office):

15. SECURITY CLASS. (of this report): Unclassified

15a. DECLASSIFICATION/DOWNGRADING SCHEDULE:

16. DISTRIBUTION STATEMENT (of this Report):

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report):

18. SUPPLEMENTARY NOTES:

19. KEY WORDS (Continue on reverse side if necessary and identify by block number):

Choice, Decision Making, Cognitive Effort, Strategies

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

We examine the effort required to execute decision strategies, and propose a set of elementary information processes (EIP's) (e.g., reads, additions, comparisons) as a common language for describing these strategies. Based upon these component processes, a model for measuring the effort required to execute a decision strategy is proposed. The model suggests that effort is a weighted sum of EIP's. We test this model and several alternatives by attempting to predict 1) decision latencies, 2) subjective reports of effort, and 3) choice errors. The proposed EIP model provides good predictions and outperforms

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S/N 0102-LF-014-6601

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competing models for response time and subjective effort. Estimates of the time and effort associated with each EIP seem plausible and consistent with those found in other cognitive tasks. On balance, the EIP approach to conceptualizing and measuring the effort of executing a choice strategy receives strong support.

In many cognitive tasks, such as problem solving (Simon, 1975), solving analogies (R. Sternberg, 1977), and answering questions (Reder, 1982), individuals appear to employ a variety of different strategies. Nowhere is this variability in strategy use so apparent as in decision-making. A major finding of the last decade of decision research is that an individual may use many different kinds of strategies in making a decision, contingent upon task demands (Payne, 1982).

Given the evidence for the use of multiple strategies in such a diverse set of cognitive tasks, a fundamental issue is how people decide what to do. This concern with how problem solvers and decision-makers select a strategy is reflected in the growing concernw ith the regulation of cognition and "metacognition" (Brown, Bransford, Ferrara, & Campioni, 1983).

An approach advocated by many researchers is to look at various strategies as having differing advantages and disadvantages, and hypothesize that an individual might select the strategy that is, in some sense, best for the task. For example, Siegler notes that "Children (and adults) have good reasons to use multiple strategies. Strategies differ in their accuracy, in how long they take to execute, in their demands on processing resources, and in the range of problems to which they apply. (p. 1)" Theorists studying decision behavior have expanded upon such ideas and have explicitly viewed selection among decision strateies as a tradeoff between (1) the amount of cognitive resources (mental effort) required to use each strategy, and (2) the ability of each strategy to produce an "accurate" response (Beach and Mitchell, 1978; Johnson and Payne, 1985; Russo and Dosher, 1983; Wright, 1975).

The general notion that different processing strategies require different amounts of computational effort to execute seems obvious in the

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domain of decision making. The decision strategy of expected utility maximization, for instance, requires a person to process all relevant problem information and to trade off values and beliefs. The lexicographic choice rule (Tversky, 1969), on the other hand, chooses the alternative which is best on the most important attribute, ignoring much of the potentially relevant problem information. Thus, there appear to be clear differences among decision strategies in the amount of information that is processed in making a choice.

At a more precise level of analysis, however, a comparison among decision strategies in terms of mental effort is much more difficult. In part this is because the decision strategies that have been proposed in the literature have varied widely in terms of their formal expression. Some have been proposed as formal mathematical models (e.g., elimination-by-aspects, Tversky, 1972), and others as verbal process descriptions (e.g., the majority of confirming dimensions rule, Russo & Dosher,1983). What is needed is a language that could be used to express a diverse set of decision strategies in terms of a common set of cognitive operations. Such a language would also allow a more detailed analysis of the components of processing (effort) involved when a particular decision strategy is used to solve a particular decision problem. In other words, one could examine whether the amount of information to be processed is the major determinant of effort, or whether the specific mix of cognitive operations which is utilized affects effort.

Another difficulty facing such cost-benefit approaches, in addition to conceptualizing effort, is actually measuring the effort associated with a given strategy. There have been a number of measurement techniques proposed for the related concept of mental workload (Gopher & Donchin, in press; Wickens, 1984), ranging from self-reports to physiological measures. However,

the different measures of workload, such as response latencies, secondary tasks, error rates, or self-reports, do not always agree. Hence, Gopher and Donchin (in press) recommend the use of a battery of multiple measures, along with a detailed theoretical analysis of the expected workload of a task.

The primary purpose of this paper is to examine the effort required to use various decision strategies in choice environments that vary on several dimensions. We first develop a metric of decision effort based on the concept of elementary information processes (Chase, 1978; Newell & Simon, 1972). We then use this componential approach to modeling decision effort to predict multiple indicators of strategy execution effort: decision latencies, self-reports of task difficulty, and errors in strategy execution. The independent variables used include measures based upon the proposed componential approach to decision effort as well as some alternative models. Our goal is not to propose a complete theory of mental workload, but to illustrate an approach to measuring the execution effort of choice strategies. Such an approach may allow us to better understand when a particular decision strategy will be used to solve certain decision problems.

A secondary goal of the current research is to provide evidence that decomposition in general is a useful concept in decision-making. While commonplace throughout much of cognitive psychology, the notion of dividing strategies into a small set of shared components is relatively untested in decision-making.

In the following section, previous attempts to conceptualize and measure decision effort are briefly addressed, and the proposed approach is outlined. Then the methodology and results of a study designed to test this approach are described in detail.

Measuring Decision Effort

The theoretical construct of mental effort has a long and venerable history in psychology (Kahneman, 1973; Navon & Gopher, 1979; Thomas, 1983). However, there have been only a few attempts to model and compare decision rules in terms of an effort metric.

Two studies that attempted to directly measure the execution effort of various decision rules are Wright (1975) and Bettman & Zins (1979). In each study, subjects were instructed to use particular decision rules to solve certain problems. The percent of correct judgments using the rules and self-reports of task difficulty or ease of use were obtained in both studies. In addition, Bettman and Zins obtained a measure of the time taken to apply a rule to a problem. The results clearly show that certain rules were perceived as less effortful then others. For example, a lexicographic rule was generally perceived as less effortful than other decision rules. That rule also tended to be the most accurate and quickest in its execution. However, these two studies had significant limitations. First, neither study employed a method beyond initial instruction to ensure that subjects actually used the prescribed decision rules. Second, neither study provided a conceptual basis (model) for why a certain decision rule would be expected to be more or less effortful in a particular task. That is, neither study attempted to model the components of decision-making effort.

Shugan (1980) suggested an effort metric based upon one operation, the binary comparison of two alternatives on an attribute. More effortful decisions involved more comparisons. Shugan also showed that the effort of strategies would vary with certain task characteristics like the correlational structure among attributes. Unfortunately, using the binary comparison as the fundamental unit of effort restricts Shugan's analysis to certain decision

rules. However, Shugan's work implies that any approach to modeling strategy effort must be sensitive to the joint effects of strategy and task.

Based upon the work of Newell and Simon (1972), Huber (1980) and Johnson (1979) offered decompositions of choice strategies using more extensive sets of components. Each independently suggested that decision strategies be described by a set of elementary information processes (EIP's). A decision rule or strategy was represented as a sequence of mental events, such as reading a piece of information into STM (short-term memory), multiplying a probability and a payoff[1], or comparing the values of two alternatives on an attribute. Johnson and Payne (1985) employed a similar set of EIP's for decision making, shown in Table 1, and constructed production system implementations of several different choice strategies.

We propose this set of EIP's as underlying components from which various decision strategies can be constructed. That is, we assume that a set of EIP's like those in Table 1 is at a sufficient level of detail to provide a common language to describe the diverse set of decision strategies that exist. Furthermore, we propose that by using such EIP's to describe strategies at the componential level, meaningful comparisons among strategies in terms of decision effort can be made.[2]

Insert Table 1 about here

Given a decomposition of decision strategies into a common set of components, a general measure of decision effort is the number of component EIP's required to execute a particular strategy in a particular task environment. This notion of measuring decision effort in terms of the number of EIP's builds on an idea for measuring processing effort proposed by Newell and Simon (1972). Empirical support for this approach has been provided by

showing a relationship between the predicted number of EIP's used and response times for a variety of cognitive tasks (Card, Moran, & Newell, 1983; Carpenter & Just, 1975).

To validate this particular proposed decomposition into EIP's, we examine several alternative models. Specifically, we investigate several models of decision effort in a setting where subjects make choices for six sets of twenty decision problems varying in size and other factors, using a different decision strategy for each set. The simplest model of decision effort in terms of EIP's would be to treat each component process as equally effortful and simply sum the numbers of each component process to get an overall measure of effort. Alternatively, the effort required by individual components could be estimated and the tally for the individual operations weighted by those estimates before summing across all components. In this study we will examine both of these versions of the componential approach to measuring decision effort in terms of EIP's.

Alternative models of effort not based on the componential approach are also considered. At the structural level, we characterize effort as a function of task complexity (number of alternatives and attributes) and the particular strategy used. Next, we investigate a model of effort based on the number of items of information processed by a particular strategy in a choice environment. Since it is easy to monitor information acquisition behavior, this might be called an explicit behavioral model of strategy effort. Third, we will examine EIP models of decision effort based upon the conceptualization of the underlying components of decision processes outlined above. Finally, we explore models of decision effort that combine the EIP concept with additional factors, such as the task complexity variables and individual differences variables.

Each model of strategy effort will be investigated using three indicators of execution effort: (1) the time to make a response, (2) self-reports of effort, and (3) the number of errors in the execution of a strategy. For the models using response times as the measure of effort, analyses can be carried out at different levels of aggregation: the overall decision, acquisitions of individual items of information, and intermediate levels of aggregation (e.g., total time spent on each individual alternative (Card, Moran, & Newell, 1983)). The overall goal of performing these multiple analyses using different models of effort, different indicators of effort, and different levels of aggregation is to attempt to determine the most appropriate conceptualization for measuring the effort required to execute decision strategies. We hypothesize that the componential approach described above will provide the best fits to the data across the varying levels of analysis. If the componential approach can be shown to be both robust over different indicators of effort and different levels of aggregation, and at the same time superior to alternative models, we will have provided strong support for this approach to conceptualizing decision making effort.

Method

Overview

Subjects were trained to use six different decision strategies for making these decisions. Each strategy was used in a separate session to make twenty decisions for decision problems ranging in size from two to six alternatives and from two to four attributes. Subjects used a computer-based information acquisition system to acquire information and make decisions among sets of alternatives. The computer-based acquisition system monitored the subjects' information sequences; recorded latencies for each acquisition; recorded the overall time for each problem; and recorded any errors made by

the subject (i.e., departures from the prescribed search pattern or choice). In addition, subjects rated the difficulty of each choice and the effort each required on two response scales presented at the end of each decision problem.

The data recorded by the computer-based acquisition system provided for three major types of dependent variable: response times, self-reports of effort and difficulty, and observations of errors in execution of a strategy. Three basic models were used to generate independent variables: structural, behavioral, and EIP, as noted above. These models were then used to predict the three types of dependent measures. Regression models were used for the response time and self-report data, and logistic regressions were used to predict the error data. Finally, for the response time data, the EIP model analyses were performed at three levels of aggregation: the overall time for each problem, the time for each individual acquisition, and the aggregate times spent on each alternative and on each attribute in a problem (e.g., seven separate times for a four alternative, three attribute problem).

We describe the details of the methodology as follows: first, the six decision strategies used are described, followed by a description and examples of how the EIP counts were generated. Then the generation of the sets of twenty decision problems is discussed, followed by details on the computer-based acquisition system. Finally, the experimental procedure is discussed in detail, preliminary analyses are reported, and an overview of the major analyses performed is presented.

Decision Strategies

Rules Used. Six different decision strategies were used in the experiment: weighted additive; equal weighted additive; lexicographic; elimination by aspects; satisficing (conjunctive); and majority of confirming dimensions. Each of these rules was implemented as a production system model

(for examples see Johnson and Payne 1985; Payne, Bettman, and Johnson, 1986). These particular rules were selected for two reasons: 1) each rule has been a focus of previous research on choice processes; and 2) this set of rules provides a broad coverage of the set of basic elementary operations (EIP's) used as the components in our conceptualization of strategy execution effort. We first describe the strategies, and then the elementary operations are considered.

To facilitate our description, we first outline a typical choice problem. A choice problem consists of a set of alternatives, each of which is described on several attributes, or criteria. In this study, the alternatives were job candidates, and the attributes were scores, or ratings, on various selection criteria (e.g., leadership potential and motivation). The decision problems had from two to six candidates, each described by from two to four criteria. For each attribute, an importance weight and a cutoff value specifying a minimally acceptable level for that attribute were also displayed. Different decision strategies might use both weights and cutoffs, one of the two, or neither, as described below.

The <u>weighted additive</u> rule requires the subject to develop an evaluation for each alternative by multiplying each weight times the attribute rating and adding those products for all attributes. The alternative with the highest evaluation is selected. In the <u>equal weighted additive</u> model, the evaluation for each alternative is obtained by adding the ratings for all the attributes, with the alternative with the highest evaluation selected. No weights or cutoffs are used.

The <u>lexicographic</u> rule requires the subject to first find the most important attribute (the attribute with the largest weight) and then search the values on that attribute for the alternative with the highest value. That

alternative is selected, unless there are ties. In this case, those tied alternatives are examined on the second most important attribute. That process continues until a winner is found.

The elimination by aspects (EBA) strategy also begins by determining the most important attribute and examining that attribute's cutoff value. Next, all alternatives with ratings below the cutoff for that attribute are eliminated. This process continues with the second most important attribute, and so on, until one alternative remains. The satisficing (conjunctive) rule requires the subject to consider one alternative at a time, comparing each attribute to the cutoff value. If any attribute is below the cutoff value, that alternative is rejected. The first alternative which has values which pass the cutoff for all attributes is chosen.

Finally, the majority of confirming dimensions rule (MCD) processes pairs of alternatives. The values of the two alternatives are compared for each attribute, and a running evaluation is kept: if the first alternative has a greater value on an attribute than the second, one is added to the score; if the second alternative is greater, one is subtracted; if the two alternatives are tied, the score is not changed. After all attributes have been examined, if the score is positive, the first alternative is retained; if the score is negative, the second alternative is retained; and if the score is zero, the alternative winning the comparison on the last attribute is retained. Thus, the general idea is to retain the alternative which is better on the most criteria. The alternative which is retained is then compared to the next alternative remaining among the set of alternatives. If no other alternative remains, the retained alternative is selected.

Calculating EIP Counts

To describe the steps a subject followed in more detail and to show how EIP counts were determined, we first consider the particular EIP's used and then present two more detailed examples of rules applied to a particular decision problem. The major EIP's utilized were MOVES, READS, ADDITIONS, PRODUCTS, COMPARES, ELIMINATIONS, and DIFFERENCES. A MOVE involves moving to another piece of information, while a READ consists of acquiring that information (moving it to short term memory). Since MOVES and READS are in general perfectly correlated, we will only consider READS (acquisitions) in this study. ADDITIONS, PRODUCTS (of weights and ratings), and DIFFERENCES are self-evident. COMPARES involved comparing two pieces of information and determining the larger (two ratings, two overall alternative scores, two weights, a rating and cutoff, etc.). Finally, ELIMINATIONS could be either discarding an attribute (because it had already been used) or an alternative (because its score was surpassed, it failed a cutoff, etc.).

Examples. Two examples will be considered in more detail, a weighted adding case and an EBA example. Before doing this, however, some general comments are in order. First, the number of EIP's required for a particular decision is a function of the specific rule used, the size of the problem (the number of alternatives and attributes), and the specific values of the data. Rules which examine all of the ratings for each alternative, such as the weighted adding rule, need more EIP's than rules which may process only part of the data, such as the EBA rule. Larger problems also tend to require more EIP's. Problems with more values which surpass cutoffs will also generally require more EIP's. Second, in the specification of the rules, an attempt was made to take advantage of the left to right, top to bottom natural reading order.

Insert Table 2 about here

For the weighted adding rule, consider the 4 alternative, 3 attribute decision problem shown in Table 2. The numbers in parentheses are labels that will be used for convenience for identifying the sequence of acquisitions in the following. Subjects were instructed to acquire the first weight (1) and then the rating on the first attribute (4). They then multiplied these two numbers and retained the score. This process was repeated (sequence (2), (5), (3), (6)) until alternative A was finished. For the first alternative, the total score of 60 was simply retained as the current best. After processing the first alternative, there would be six READS, three PRODUCTS, two ADDS, and no COMPARISONS, DIFFERENCES, or ELIMINATIONS. For alternative B, the sequence would be (1), (7), (2), (8), (3), (9). Then the total score for B, 44, would be compared to the current best, and the current best of 60 would be retained. The assumption was made that in the comparison of total scores, the losing alternative was not explicitly eliminated. Rather, the subject would merely store the one retained. Thus, after two alternatives we would have twelve READS, six PRODUCTS, four ADDS, one COMPARISON, no DIFFERENCES, and no ELIMINATIONS. This process would be repeated for the remaining two alternatives (sequence (1), (10), (2), (11), (3), (12), (1), (13), (2), (14), (3), (15)). Hence, the production system model predicts that in total this problem would require 24 READS, 8 ADDITIONS, 12 PRODUCTS, 3 COMPARISONS, no DIFFERENCES, and no ELIMINATIONS.

Insert Table 3 about here

The example of a three alternative, four attribute problem shown in Table 3 is used to clarify the EBA rule specification. The subject had to

first find the most important attribute. This was done by starting with the first weight and comparing it to the second, retaining the larger (the second). The second was then compared to the third, and the second was retained. Then the second was compared to the fourth, and the fourth (experience) was retained as the most important attribute. The sequence of acquisitions would thus be (1), (2), (3), (4). There would be four READS and three COMPARISONS. Then the subject acquired the cutoff for experience and examined the value for all alternatives on experience, comparing each value to the cutoff and eliminating any alternative not passing the cutoff. In this case, the sequence would be (8), (12), (16), and (20), with alternative C eliminated. The total EIP's thus far would be eight READS, six COMPARISONS, and one ELIMINATION. Then the experience attribute would be eliminated, and the weights for the remaining three criteria would be acquired and compared, resulting in motivation's being selected as the second most important attribute (sequence (1), (2), (3)). Then the cutoff for motivation was acquired and the values for the retained alternatives, A and B, were compared to the cutoff (sequence (6), (10), (14)). At this point, there would be a total of 14 READS, 10 COMPARISONS, and two ELIMINATIONS. Both A and B passed the cutoff, so the subject would then eliminate the motivation attribute and return to the weights to determine the third most important remaining attribute, leadership (sequence (1), (3)). Then the cutoff for leadership was examined, A and B were compared to the cutoff, and A was eliminated. B would then be chosen (sequence (5), (9), (13). In total, there would be 19 READS, 13 COMPARISONS, and four ELIMINATIONS (two attributes and two alternatives).

These examples illustrate two principles: the number of EIP's varies with problem size and with the particular values used, and different rules use different subsets of the EIP's. With regard to the second point, the weighted

adding rule uses READS, ADDITIONS, MULTIPLICATIONS, and COMPARISONS; the equal weighted adding rule uses READS, ADDITIONS, and COMPARISONS; the lexicographic rule uses READS, COMPARISONS, and ELIMINATIONS; the EBA rule uses READS, COMPARISONS, and ELIMINATIONS; the satisficing rule uses READS, COMPARISONS, and ELIMINATIONS; and the MCD rule uses READS, ADDITIONS, COMPARISONS, ELIMINATIONS, and DIFFERENCES.

It should also be noted that certain rules (weighted adding, equal weighted adding) have the same EIP counts for any problems of the same size (i.e., with the same number of alternatives and attributes). On the other hand, the other rules (lexicographic, EBA, satisficing, and MCD) can have different EIP counts even for problems of the same size, depending upon the particular values of the data. This property of the rules affected the selection of decision problems for the experiment, as discussed next.

Selection of the Decision Problems

As noted above, subjects completed twenty decision problems for each of the six decision rules. These decision problems were generated by taking several factors into account. First, pilot studies revealed that numbers of attributes greater than four were extremely difficult for subjects, particularly for the weighted adding rule. Second, numbers of alternatives greater than six caused crowding problems on the computer display used in the information acquisition system. Hence, decision problems with from two to six alternatives and two to four attributes were used. This generated 15 possible sizes, ranging from two alternatives and two attributes to six alternatives and four attributes.

For the weighted adding and equal-weighted adding rules, since problem size determines the EIP count, one problem of each size was included, making fifteen decision problems. Then five problem sizes were randomly selected to

complete the twenty decision problems. Values for the weights and ratings were assigned randomly, with the restriction that no overall scores for alternatives in the same problem set were tied.

For the remaining rules, several problems were generated for each problem size that represented low, intermediate and high EIP counts for that size (e.g., for a three alternative, four attribute EBA problem, elimination of two alternatives on the first attribute would lead to a low count, retention of all three alternatives until the last attribute would be a high count, and the operations used for the example described above might be an intermediate count). Then sets of twenty problems were randomly selected for each rule from the total set of forty-five size/count combinations.

The random selection procedure just described was repeated many times in an attempt to deal with correlation problems among the EIP counts. Since the EIP counts were to be used as independent variables in models to predict decision times, effort self-reports, and errors, it was desirable that their intercorrelations across all 120 decision problems should be as low as possible to avoid multi-collinearity problems (Kmenta 1971). As noted above, however, certain rules use only some EIP's and not others, so there are some correlations that will be high because of the definition of the rules. For example, the correlation between COMPARISONS and ELIMINATIONS will tend to be high because rules with no ELIMINATIONS (e.g., the adding rules) tend to do very few COMPARISONS, whereas rules with many COMPARISONS also have more ELIMINATIONS. To minimize these intercorrelation problems, we repeated the random selection procedure 1,000 times, and selected the set of 120 decision problems with the smallest intercorrelations. The resulting intercorrelations are shown in Table 4. We were unable to further reduce the highest, COMPARES and ELIMINATIONS, for the reasons outlined above. Although these

intercorrelations will present some interpretation problems for the analysis of the overall decision times, the EIP's at other levels of aggregation have lower intercorrelations.

Insert Table 4 about here

The Computer-Based Information Acquisition System

A computer-based information acquisition system was utilized in carrying out the experiment. A software system for personal computers, Mouselab (Johnson, Payne, Schkade, & Bettman, 1986), was developed to monitor information acquisition patterns and decisions of subjects. Mouselab can present several different types of information displays to subjects. In this study, the subject saw a matrix display on the computer monitor for each decision problem. The rows of the matrix were labeled weights, cutoffs, and then the names of the alternatives to be considered. The columns were labeled with the names of the attributes. At the bottom of the monitor screen were boxes used to indicate choice of an alternative (hence termed choice boxes). For an example of this display, see Figure 1.

Insert Figure 1 about here

Initially, the matrix display provides only the labels for the rows and columns and the choice boxes. The information is hidden in the blank cells on the screen. To acquire information, the subject must move a cursor controlled by the mouse to the desired cell of the matrix. The cell then opens, displaying the information. For each decision, the subject would use the mouse to acquire the appropriate information in the sequence specified by the current strategy. Mouselab recorded the sequence in which cells were opened and the time spent in each cell. The time measurements use the system clock

of the personal computer, providing a resolution of approximately 17 milliseconds. After the requisite information had been examined, the subject moved to the appropriate choice box and clicked a button on the mouse to designate the chosen alternative. Mouselab can also present response scales and text instructions to subjects, as noted below.

A crucial feature of Mouselab for the present study is the ability to monitor the sequence of acquisitions made by a subject. Since the EIP models of effort we propose required EIP counts for each problem, it is crucial that subjects use the strategy exactly as it is specified, so that the EIP counts can be predicted accurately. For example, to ensure that the EIP counts for the weighted adding and EBA examples given above are correct, we must monitor that subjects follow the exact acquisition sequence for each rule. Mouselab includes a move monitoring feature, which allows the correct sequence of cells to be specified for each decision problem. If the subject enters a "wrong" cell, the cell will not open, and after two seconds the computer will emit an audible buzz. The attempt to enter an incorrect cell is also recorded in the output information about the subject's move sequence. Hence, trials where a specified number of incorrect moves has occurred can later be discarded or analyzed as error trials if desired.

A mouse-based information acquisition system was used for several reasons. Card, Moran, and Newell (1983) compared the mouse, joystick, and two keyboard-based devices. They found that the mouse was easy to learn, was significantly faster than the other devices, and had a lower error rate. An analysis of a typical decision task for this study using Fitts Law indicates that subjects could move between information cells in less than 100 milliseconds. This suggests that the time to move the mouse is limited mainly

by the time it takes to think where to point, not the movement of the mouse itself.

Procedure

Overview. Subjects participated in eight separate sessions over a period of several days. Each session lasted from one to one and a half hours. No more than two sessions were run in one day, and separate sessions were at least four hours apart. The first session taught subjects the decision rules and familiarized them with the computer-based information acquisition system. In each of the subsequent six estimation sessions, a subject made twenty choices using a different specified rule. The order of the rules was randomized across subjects. The final session had twelve choice problems where the subject was free to use any strategy desired. These "free" choices are not analyzed further in this report.

Subjects. Subjects were seven adults, ranging in age from 21 to 34, and included four males and three females. They varied in their prior awareness of the decision making literature, ranging from graduate students who had studied decision making to non-students who had never been exposed to those concepts.

Training. It was crucial that subjects thoroughly learn the six decision strategies to be used (weighted adding, equal-weighted adding, lexicographic, elimination by aspects, satisficing, and majority of confirming dimensions) and learn to use the mouse-based acquisition system. Hence, a familiarization session was developed. Subjects were first introduced to the mouse and were shown how to use it to open the cells, respond to various response scales, and indicate a choice. After practicing these tasks, subjects were next given a training session for the decision rules which was developed using the Mouselab system.

The subject was first informed about the type of decision problem to be presented. He or she was informed that the decisions to be made were personnel decisions involving selection of job candidates. These selections were to be made according to the rules specified by different divisions of their company, and the sets of candidates might have both differing numbers of candidates and different amounts of information on each candidate. Subjects were then told that information on up to four attributes might be presented: leadership potential, creativity, job experience, and motivation. The left to right ordering of the subset of these attributes used on any given trial was randomized.

Following this overview of the problem setting, subjects were introduced to the ratings used to describe each candidate on each attribute. Ratings ranging from 2 (poor) to 7 (excellent) were used as the information in each cell. Subjects were next introduced to the ideas of importance weights for the attributes and cutoffs for the attributes. They were then asked to select the most important attribute and to pick candidates surpassing a cutoff to provide training using these ideas. These concepts were then reviewed before the decision rules were introduced.

For each rule, the subject was first given a thorough written description of the rule on the computer monitor. Then the subject was given several decision problems and told to apply the rule using the mouse. The move monitoring system was used on the last trial to inform subjects of mistakes. The subject was also told what the correct choice using the rule should have been. Thus, subjects had accuracy feedback on both the sequence of acquisitions and their choices during training. Following these practice trials, the next rule was presented. The rules were presented in the familiarization session in an order ranging from simple to more complex:

equal-weighted adding, lexicographic, satisficing, elimination by aspects, weighted adding, and majority of confirming dimensions.

Finally, after all six rules had been presented, subjects were given six practice trials, one for each rule. These trials introduced the use of two response scales to measure the difficulty of the decision task and how effortful the decision was. The first scale asked the subject to rate how difficult the choice was to make on a scale ranging from 0 (not difficult at all) to 10 (extremely difficult). The second scale asked the subject to rate how much effort he or she put into making the choice on a scale ranging from 0 (hardly any effort) to 10 (a great deal of effort). The purpose of these six practice trials was threefold: 1) to introduce the response scale; 2) to consolidate the learning of the rules; and 3) to introduce subjects to the range of difficulty in the problems so that they could calibrate their use of the response scales more accurately during the actual estimation sessions. This latter purpose was accomplished by selecting a variety of problem sizes and difficulty levels for the six practice trials.

Estimation Sessions. At the beginning of each session, the subject was given a review of that session's decision rule. The rule was described again, and several practice trials were given, with feedback on the accuracy of the acquisition sequence and choice. Then subjects were given a sequence of decision problems where they had to make two consecutive choices using the rule with no errors in acquisition sequence or alternative chosen. Following successful completion of these trials to criterion, the actual experimental trials for that session began.

As noted above, the twenty choice problems for each decision rule were presented to the subject on an IBM Personal Computer via the Mouselab software. Subjects used a Mouse systems mouse as a pointing device. These

problems were randomly ordered (the random order was the same for all subjects). For each problem, the subject followed the sequence of acquisitions implied by the rule. The move monitoring system described above was used to monitor subjects' adherence to the correct sequence for the rule. Subjects then indicated the alternative chosen, and responded to the difficulty and effort scales described above. For each choice, Mouselab recorded the sequence of acquisitions, the time of entry and exit for each cell, the alternative chosen, and values on the two response scales. The overall latencies for the choice and the two scale responses were also recorded. Finally, any errors in acquisition sequence were recorded. These data were then written to a disk file for later analysis. This process was repeated until all twenty choices had been completed for the given rule.

After completing all eight sessions, subjects received $40 for their participation. In addition, they were told that three $5 bonuses would be paid for (1) above average performance in terms of overall accuracy, (2) minimization of incorrect search, and (3) speed of decision, respectively. In other words, subjects were informed that they could earn an additional payment of up to $15 dollars depending upon their performance.

Preliminary Analyses

Before the major analyses could be performed, the data were analyzed to determine the prevalence of errors, the existence of speed-accuracy tradeoffs, and the relationship between the two self-report measures of effort.

Subjects selected incorrect alternatives on 11.4% of the trials. In addition, slightly less than 1% (.8%) of the trials contained severe deviations from the correct sequence of acquisitions specified for that trial (i.e., more than two "buzzes"), even though the correct alternative was still selected. Taken together, this yields a total of 12.2% error trials. Over

half of these errors come from the weighted adding (27.1%) and elimination by aspects (32.2%) rules. For all analyses, all error trials of both types were removed from the data. However, analyses performed when all trials were included show virtually identical results.

To examine the possible existence of speed-accuracy tradeoffs, response latency was correlated with error, both across and within strategies. Overall, the correlation between time for each decision and the probability of an error was .15 ($p<.0001$). Similar positive correlations were obtained for each rule, subject, and rule by subject combination. In no case was there a significant negative correlation, which indicated that these data are relatively free from any concerns with speed-accuracy tradeoffs.

Finally, the two self-report measures of effort and difficulty were examined. Their intercorrelation was .85, suggesting that they measure the same underlying construct. A principal components analysis showed that the first factor accounted for 93% of the variance in the scores, so the two ratings were added to form an overall index of subjective effort.

For the analyses we report, several models are estimated using different independent variables. In every model, however, dummy variables representing the subject and session (i.e., the order of that session among the six estimation sessions) are included, as are variables representing the linear and quadratic effects of trial (i.e., the order among the twenty decision problems within any session). These variables, although statistically significant, account for small portions of the explained variance and simply allow for changes in the intercept term across sessions and subjects and for any effects of practice across trials to be taken into account. Since the effects are not theoretically important for our purposes, they are not reported in the discussion of the results.

Overview of the Analyses

As discussed above, we examined three major indicators of strategy execution effort: response times, subjective reports of effort and difficulty, and errors. By use of these multiple measures, we hope to gain covergent evidence for the proposed approach to characterizing strategy execution effort in terms of EIP's.

Recall that we have described three different classes of models for effort: structural, behavioral, and EIP. The structural model attempts to describe effort solely in terms of problem characteristics: the number of alternatives and attributes, their product, and a dummy variable for each rule. The behavioral model attempts to explain effort using the only overtly observable behavior, the number of information acquisitions (READS). Finally, we examine two different EIP models: the weighted EIP model attempts to predict each dependent measure using as variables a count for each of the EIP's. Each mental operation is thus allowed to have its own characteristic effect upon the dependent measure. For example, each EIP has its own latency in the response time analyses. In contrast, the equal-weighted EIP model represents the null hypothesis, in which all EIP's are given the same weight. Such models have proven surprisingly robust (Dawes, 1979) and provide a reasonable baseline for the elementary operations model. We can assess the relative fit of each of these models and test certain comparisons.[3] All models also contain the blocking variables (Session, subject and trial) described above.

For response time, we can estimate some models at three different levels of aggregation. The overall latency for the decision; the latency for each acquisition; and, at intermediate levels, the total times spent examining each alternative and each attribute. For the overall decision times, all the

models can be estimated, using regression analysis. At the level of each acquisition, the structural and behavioral models do not make sense; hence, only the equal-weight EIP and weighted EIP models are estimated.[4] To predict the times spent on each alternative or attribute, the behavioral model, equal-weight EIP model, and weighted EIP model were estimated.[5] We examine multiple models at several levels of aggregation because it helps us deal with intercorrelation problems and also provides convergent evidence for the fit of the EIP models relative to the others regardless of the level of detail of the analysis (Card, Moran, & Newell, 1983).

For the self-reports of effort, regression analyses were performed using the structural, behavioral, equal-weight EIP, and weighted EIP models, with the index of subjective effort as the dependent measure. Since this index was only meaningful at the level of an individual decision problem, no analyses at more disaggregate levels were done.

Finally, for the error analyses, logistic regressions (Neter and Wasserman, 1974, p. 322), were used to predict the probability that a given trial would produce an error. Since the dependent variable is dichotomous (an error occurred or not), logistic regression is an appropriate technique which allows the use of all trials without having to reduce the data to proportions. Since errors are also only defined at the level of each decision problem, no analyses at disaggregate levels were performed. The structural, behavioral, equal-weight EIP, and weighted EIP models were run using the occurrence of an error or not as the dependent measure.

Table 5 summarizes these analyses across the various dependent measures, models, and levels of aggregation. In all cases, the basic hypotheses are essentially the same. The greater the number of alternatives and attributes (structural), reads (behavioral), sum of EIP's (equal-weight EIP), or weighted

sum of EIP's (weighted EIP), then the more time taken, greater subjective feelings of effort reported, and greater likelihood of execution error. Our central hypothesis is that the EIP models will provide significantly better fits than the structural and behavioral models.

Results

The degree of fit for the analyses indicated in Table 5 is summarized in Table 6. To provide the most sensitive tests of the models, these analyses were run by pooling across all seven subjects and including dummy variables for the subjects. Since these analyses use all of the data, they provide the most powerful tests for separating the various models. However, this also makes the assumption that all subjects have identical latencies for each EIP. We relax this assumption below. We examine the results for each of the three major classes of dependent variables in turn: response time, subjective effort, and errors.

Insert Table 6 about here

Response Time Analyses

Overall Decision Times. Table 6 indicates that all of the models provide good fits for the overall response times ($p < .0001$). As hypothesized, the weighted EIP model provides the best degree of fit, $R^2 = .81$. The fit of the weighted EIP model is significantly better than that of the behavioral model ($F(5, 713) = 77.8$, $p < .0001$) or that of the equal-weight EIP model ($F(5, 713) = 74.6$, $p < .0001$).[6] While the structural and weighted EIP models cannot be directly compared statistically, it is clear that the weighted EIP model provides a better degree of fit. In addition, if we add the variables from the structural model (problem size and rule dummy variables) to the weighted EIP model, the expanded model does not provide

improved fit, with an incremental $R^2 = .005$, n.s. Finally, these results hold up well in cross validation. Estimating the model on one-half of the data and using these estimates to predict the other half yields average R^2 of .63, .70, .68, and .89 for the structural, behavioral, equal-weight EIP, and weighted EIP models, respectively.[7]

Individual Acquisition Times. Given the success of the weighted EIP model at the level of overall decision times, we turn to other levels of analysis for evidence that the results obtained are consistent across levels of aggregation. However, as Card, Moran, and Newell (1983) argue, analyses at more disaggregate levels will tend to have lower absolute levels of fit, for several reasons: measurement of the exact operators employed is likely to be more errorful at lower levels of aggregation, and variation in the time required to execute operators will be more apparent when the number of EIP's for each case is smaller, as in these more disaggregate analyses. For example, while we assume that all additions take the same amount of time, it is clear that some additions (i.e. 2+2) take less time than others (i.e. 8+7). This assumption is most problematic at the more disaggregate level, where the characteristics of a single addition largely determine the latency.

In examining the fit of the equal-weight and weighted EIP models at the individual acquisition level, also shown in Table 6, it is apparent that the absolute level of fit has indeed declined, although it is still significant at $p < .0001$. The weighted cognitive model ($R^2 = .23$) still performs better than the equal-weight cognitive model ($R^2 = .16$) ($F(4, 12159) = 325.30$, $p < .0001$).

Times for Each Alternative and Attribute. The models estimated to predict the total time spent on each alternative and the total time spent on each attribute replicate those reported above (See Table 6). The behavioral and equal-weight EIP models perform roughly equally, and both provide

significantly lower fits than the weighted EIP model. For time spent on alternatives, the weighted EIP model is superior to the behavioral and equal-weight EIP models, $F(5, 2943) = 297.54$, $p < .0001$ and $F(5, 2943) = 351.02$, $p < .0001$, respectively. For time spent on attributes, the same is true, $F(5, 2313) = 204.39$, $p < .0001$ and $F(5, 2313) = 178.86$, $p < .0001$, respectively.

More Complex Models. These analyses strongly and consistently support the proposed EIP model for measuring strategy execution effort. The weighted EIP model provides the greatest degree of fit across four levels of aggregation in response times. The degree of fit at the overall decision time level is quite impressive, given the complexity of the decision tasks studied. In addition, the model comparisons allow several conclusions: 1) Models which examine structural characteristics of the task (e.g., problem size and rule dummy variables) are not sufficient; 2) Models using observable behaviors (acquisitions) alone do not suffice, so a more complete set of EIP's is necessary; 3) Each EIP should be allowed to have its own weight, as the weighted EIP model consistently outperforms the equal-weighted model.

Since the weighted EIP model seems necessary, in the sense that it provides superior fit to its three simpler competitors, we also examine whether it is sufficient. That is, will more complex models improve on the degree of fit? These models are reported only for the overall decision time analysis, but were replicated at other levels with similar results. The first complex model directly tested the hypothesis that the EIP's require the same time for each rule. This is tested by allowing the time taken by each EIP to vary from rule to rule. The weighted EIP model is then a special case of this augmented model, and the significance of the incremental fit can be tested. Although the incremental fit is significant ($F(13, 700) = 1.91$, $p < .05$), the incremental R^2 is very small, .007. Hence, as a first approximation, the

assumption that each operation requires a constant amount of time independent of the strategy in which it is used seems reasonable.

The second more complex model allows the times for the EIP's to vary across subjects. Even if individuals use the same strategy, they may differ in the amount of time required for each component process (Hunt, 1978; R. Sternberg, 1977). This model achieves an $R^2 = .90$, with significantly better fit than the weighted cognitive model (Incremental $R^2 = .09$, $F(19, 674) = 17.9$, $p < .001$).[8] Given the small number of individuals in the sample, these individual differences are not pursued further.

Thus, based upon the analyses of response times, the weighted EIP model, and hence the EIP conceptualization of decision effort, receives strong support. The EIP times appear to vary across individuals, although not across rules. Moreover, the weighted EIP model provides the best fit across all of the various analyses attempted.

Estimates of EIP Times. Since the weighted EIP model received strong support, estimates of the times for each operator are shown in Table 7. Although the estimates vary to some extent across individuals, as noted above, we will examine the pooled results for the different levels of aggregation.

Insert Table 7 about here

The estimates are generally consistent across levels, which provides increased confidence in the values. The coefficients are all positive, with most significantly so. The estimates also tend to agree with estimates for similar EIP's provided by other studies. Focusing upon the overall decision time analysis, we now consider the estimates of each operator.

The READ EIP combines encoding information with the motor activity of moving the mouse. Its estimated latency is 1.19 seconds ($t(713) = 6.55$, $p <$

.0001). This estimate is plausible, since it might consist of the movement of the mouse, estimated to be in the range of .2 - .8 seconds by Johnson, Payne, Schkade, and Bettman (1986), and an eye fixation, estimated to require a minimum of .2 seconds (Russo, 1978). ADDITIONS and SUBTRACTIONS both take less than one second, with estimates of .84 ($t(713) = 4.54$, $p < .0001$) and .32 ($t(713) = .98$, n.s.) respectively. These values are not significantly different ($t(713) = 1.03$, n.s.) and are consistent with those provided by Dansereau (1969), Groen and Parkman (1972), and others (see Chase, 1978, Table 3, p .76). Our estimate for the PRODUCT EIP, 2.23 seconds ($t(713) = 10.36$, $p < .0001$), is larger than that commonly reported in the literature.

The time for COMPARISONS is very short, .08 seconds ($t(713) = .22$, n.s.), and that for ELIMINATIONS, 1.80 seconds ($t(713) = 3.00$, $p < .01$), is relatively long. This may reflect the collinearity of COMPARES and ELIMINATIONS at the overall decision time level. There is some suggestive evidence for this in the results at the more disaggregate levels. Although the estimates for READS, ADDITIONS, PRODUCTS, and DIFFERENCES are fairly similar across levels, the COMPARISON and ELIMINATION estimates vary widely. Since the intercorrelation between COMPARISONS and ELIMINATIONS is no higher than .51 for these more disaggregate analyses, it is likely that the lower estimates for ELIMINATIONS and higher estimates for COMPARISONS found in the disaggregate analyses are more plausible.

In sum, based both upon its degree of fit and the generally plausible time estimates for the EIP's, the proposed weighted EIP model receives impressive support when response times are used as an indicator of effort. The next set of results examines the performance of the various models when subjective effort reports form the indicator of effort.

Subjective Effort Analyses

There are several reasons why subjective reports of effort are interesting as a second indicator of decision effort. First, subjective effort might tap different aspects of strategy execution effort and might not be closely related to decision latency. As Kahneman (1973) observed, two different mental tasks may take similar amounts of time, but one might be seen as much more effortful than the other. This speculation receives support in our data: the overall correlation between time and the subjective effort index is .29. Secondly, while the analysis of latency helps validate the proposed EIP conceptualization of effort, subjective perceptions of effort may be important in understanding why decision-makers avoid certain strategies. If certain mental operations are perceived to be more effortful than others, such operations may well be avoided in decision-making. Associating a typical perception of effort with these EIP's may help us better understand strategy choice. Several cogent arguments for caution in the use of subjective measures of effort should also be noted. Foremost among these is the possibility that subjects cannot accurately report demands on cognitive resources (Gopher and Donchin, 1986), or that such reports do not allow comparisons across tasks which make widely differing demands.

Model Fit. From the results shown in Table 6, it can be seen that the weighted EIP model again provides the best fit to the subjective effort data. The absolute levels of fit are lower than for the overall response latencies, but are still highly significant ($p < .0001$). The weighted EIP model provides significantly greater fit than the behavioral ($F(5, 717) = 10.52$, $p < .001$) and equal-weight EIP ($F(5, 717) = 13.32$, $p < .001$) models.

The weighted EIP model of subjective effort can also be compared to more complex models. Adding the structural variables (problem size and rule

dummies) does not improve the fit (incremental R^2 = .007, n.s.). However, as was the case for the response time analysis, allowing the effort for each operation to vary for each rule produces a small, but statistically significant, increase in fit (incremental R^2 = .01, $F(13, 704) = 2.47$, $p < .01$). Finally, and again very similar to the case for response times, allowing the effort estimates for each EIP to vary across individuals significantly improves the degree of fit (R^2 = .80, $p < .0001$).

Hence, the results essentially replicate those for response times. The weighted EIP model provides the best explanation of decision-makers' self reports of the effort associated with each decision problem, and the effort estimates appear to vary across individuals, but only slightly across rules.

Estimates of EIP Effort. Estimates of the subjective effort associated with each EIP from the weighted cognitive model pooled across subjects are given in Table 8. These estimates represent the increase in reported effort per EIP on the sum of two 0-10 scales. The largest estimate is for the ELIMINATION operator, .32. However, the high intercorrelation between ELIMINATIONS and COMPARISONS (.85) must temper any interpretation of this coefficient and the small (.04) coefficient for COMPARISONS. The PRODUCT operator, as might be expected, is seen as fairly effortful, with a coefficient of .19, while the coefficients for READS and ADDITIONS are also significantly positive. These coefficients suggest that the perceived effort associated with various EIP's may vary widely, which would help to explain why some strategies are perceived more favorably than others in situations where subjects are free to select their own strategies.

Error Analyses

A final indicator of strategy execution effort is errors in strategy execution, under the hypothesis that greater required effort leads to a higher

probability of making an execution error. The logistic regression results for the error analysis are given in Table 6. The pseudo-R^2 reported in the table is analogous to an F-test in regression, and nested tests of competing models can also be conducted using tests for differences in χ^2.

From the results, we see that the weighted EIP model again performs better than the behavioral model ($\chi^2(5) = 11.43$, $p < .05$) and marginally better than the equal-weight EIP model ($\chi^2(5) = 9.15$, $p = .105$). This largely replicates the findings for time and subjective effort. However, and in contrast to those earlier findings, the structural model performs better than the weighted EIP model in terms of fit. In addition, adding the structural variables to the weighted EIP model improves its fit ($R^2 = .69$, $\chi^2(8) = 27.87$, $p < .001$). Thus, errors appear to depend not only on the proposed measure of strategy execution effort but on the size of the choice problem. Hence, errors may involve aspects of strategy execution not directly captured by the EIP's considered here. In particular, these EIP's may not capture various "bookkeeping" aspects of decision strategies, such as remembering the current best or which alternatives and attributes have been eliminated. Such aspects may increase with the size of the problem and lead to greater likelihood of an execution error.

Discussion

The concept of effort plays a major role in attempts to understand the contingent use of processing strategies. An approach to measuring the effort associated with different decision strategies is proposed in this study, using a set of elementary operators (i.e., READS, ADDITIONS, COMPARISONS, PRODUCTS, DIFFERENCES, and ELIMINATIONS) as a common "language" for describing decision strategies. This is used to generate a metric of the effort required to execute a decision strategy in terms of the number of EIP's involved.

The empirical results yielded strong support for this proposed componential approach to strategy effort. A model of effort based upon weighted EIP counts (the weighted EIP model) was found to provide the best predictions of response times at several different levels of aggregation and of self-reports of effort, two different measures of decision effort. The weighted EIP model also provided good fits to another indicator of effort, error data. In addition to this absolute level of fit, the weighted EIP model also was statistically superior to a behavioral model using only reads and to an equal-weight EIP model for each of the three indicators of effort. The weighted EIP model was also superior to a structural model using predictors based upon problem size for the response time and self-reported effort data, although the structural model was superior for modeling errors. Taken together, these results imply that a small number of simple operators can be viewed as the fundamental components from which decision rules are constructed (Bettman and Park, 1980). Whether the current set of proposed operators is sufficient is open to debate, based upon the error results, but the important point is that an EIP approach seems highly promising.

In addition to the support obtained from the overall levels of fit, the estimates of time taken for each EIP were mostly plausible and in line with prior research, hence providing additional confidence in the approach. Similar estimates also generally emerge as the analysis is repeated at different levels of aggregation. Significantly, the estimates also appear to remain essentially the same regardless of the strategy used. However, there do appear to be significant individual differences in the times taken for the individual EIP's. For example, for some individuals, arithmetic operators may be relatively more difficult than comparisons; for others the difference may be less pronounced or even reversed. This implies that individuals may choose

ifferent rules in part because the different component EIP's may be elatively more or less difficult or effortful across individuals. Although he number of subjects was too small to consider these issues in the current research, they offer intriguing possibilities for future research.

Another contribution of the study is more methodological. The Mouselab decision-monitoring software and hardware worked exceptionally well in providing detailed data about the decision task. The ability to monitor the sequence of acquisitions, measure latencies, and in general maintain experimental control over the choice task makes this system potentially very valuable for a variety of research issues in decision making and other areas of cognition.

The attainment of experimental control, necessary to predict the operators used and implement the proposed EIP models of effort, is not without costs. Subjects do not select strategies; rather, they apply given rules. Hence, the task eliminates many difficult problems normally faced by individuals making decisions. Subjects did not have to select or construct a strategy, and the sequence of operations was specified. Thus, they did not have to engage in possibly effortful control processes determining what to do next. In addition, by providing all of the weights, cutoffs, and ratings, the need for potentially difficult valuation processes was eliminated. Finally, some of the timing estimates are undoubtedly affected by the specific apparatus used (i.e., the matrix display and the mouse). Further research relaxing these restrictions on processing flexibility would be desirable. However, maintaining sufficient experimental control is essential for research at this level of detail regarding decision effort.

A second set of caveats is that although an approach which breaks down decision strategies into more detailed components seems to be strongly

supported as an approach to measuring decision effort, we have focused on a particular level of detail in taking such an approach. For example, one could model multiplications in terms of underlying arithmetic operations (e.g., Dansereau, 1969; Lopes, 1982). In addition, one could extend our models to include EIP's that model short-term memory load and other mental "bookkeeping" operations. The error analyses provide a hint that such an extension to the models used would be fruitful, but a demonstration awaits future research.

The proposed weighted EIP model appears to provide a good approach to measuring decision effort. To examine strategy selection, however, one must also consider the accuracy of a strategy in terms of the goodness of the choices made. Since strategies were specified in the current study, not chosen, there were no data available on accuracy in the above sense. However, the effort models can provide important input regarding accuracy-effort tradeoffs. The EIP time estimates, for example, could be used to model effort in simulation studies which have examined accuracy-effort tradeoffs (e.g., Johnson and Payne, 1985; Payne, Bettman, and Johnson, 1986). These estimates might also be used to predict strategy selection across decision problems or individuals, particularly if individuals were trained on a variety of strategies and constrained to select one. These selections could be modeled based upon predicted effort, the relative accuracy of the strategies, and any experimental variables affecting the weights given to accuracy versus effort.

The approach to measuring cognitive effort developed in this paper may also have applied value. For example, recently it has been suggested that the use of nutritional information in the supermarket by consumers might be improved by decreasing the effort costs associated with processing that information (Russo, Staelin, Nolan, Russell, and Metcalf, 1986). The methodology developed in this paper could be used to test the impact of

different information displays on the use of a preferred decision strategy. A related area of application would be the design of computer-based decision aids (Keen & Scott-Morton, 1978).

As a final point, research on decision making is a field of study that has drawn from cognitive psychology, but has not been as integrated into cognitive psychology as it might be (See Pitz, 1977, for a discussion of why such a schism may exist). The issues of measuring strategy execution effort and contingent strategy use in making a decision or solving a problem, however, are ones where the two fields might benefit from a closer interaction. The present investigation draws upon ideas of decomposition, chronometric techniques, and error analysis that have proved successful in understanding performance in a variety of cognitive tasks. On the other hand, characterizing factors affecting strategy, effort, accuracy, and selection across individuals and problem characteristics in various cognitive tasks may benefit from the extensive work on contingent decision strategies that currently exists. The results of the current research on modeling decision effort demonstrate that such a partnership can be highly fruitful. Hopefully, this will encourage further research efforts of this sort.

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The research reported in this paper was supported by a contract from the Engineering Psychology Program of the Office of Naval Research. The order of authorship is arbitrary. Each author contributed equally to all phases of this project. Requests for reprints should be sent to James R. Bettman, Center for Decision Studies, Fuqua School of Business, Duke University, Durham, North Carolina 27706.

Footnotes

[1]Note that the adjustment of values by probabilities or decision weights implied by the PRODUCT operator in Table 1 may not involve a literal multiplication of two quantities; rather, they may be combined by some more basic analogical process which adjusts the value of one quantity given another (Lopes, 1982). For computer simulations of choice strategies as production systems based upon collections of such EIPs, see Johnson and Payne (1985).

[2]Another advantage of the decomposition approach to decision strategies is that it expresses choice strategies using elementary processes similar to those used for describing other cognitive tasks. If EIP's possess essentially the same properties across a variety of problem solving tasks, the integration of decision research with research in other areas of cognitive psychology would be facilitated. Chase (1978) provides a more general discussion of using the EIP concept in the analysis of information processing across a variety of cognitive tasks.

[3]The behavioral model and the equal-weight EIP model are special cases of (or nested within) the weighted EIP model. Hence, the additional fit provided by the weighted EIP model over each of these two simpler models can be tested statistically (Neter and Wasserman, 1974, p. 89).

[4]For the individual acquisitions, the EIP's involved can be predicted. For example, in the weighted adding example provided above, when a rating is acquired, a READ, a PRODUCT, and possibly an ADDITION (if it is not the first attribute) are performed. Since every acquisition has a READ, the behavioral model cannot be used, and the READ operator cannot be used in the weighted EIP model. Also, it is not clear how to relate the overall problem size to predictions for each acquisition.

[5]Since these analyses aggregate over different numbers of acquisitions or each problem size and rule, the behavioral model can again be estimated

[6]The degrees of freedom for the numerator in these comparisons represent ne difference between the use of six EIP variables for the weighted EIP model nd one variable for the behavioral and equal-weight EIP models. The degrees f freedom for the denominator reflect the total trials and the total number f variables used for the weighted EIP model (Neter and Wasserman, 1974, p. 9).

[7]All of these analyses were repeated deleting the observations with the argest latencies. The results were essentially identical.

[8]Models of overall decision times were run for each of the seven ubjects, with degrees of fit ranging from .72 to .97. The average degree of it was .71, .77, .77, and .89 for the structural, behavioral, equal-weight IP, and weighted EIP models respectively. Thus, these results essentially eplicate the analyses pooling across subjects reported in Table 6.

Table 1

Elementary EIP's Used in Decision Strategies

READ	Read an alternative's value on an attribute into STM
COMPARE	Compare two alternatives on an attribute
DIFFERENCE	Calculate the size of the difference of two alternatives for an attribute
ADD	Add the values of an attribute in STM
PRODUCT	Weight one value by another (Multiply)
ELIMINATE	Remove an alternative or attribute from consideration
MOVE	Go to next element of external environment
CHOOSE	Announce preferred alternative and stop process

Table 2

Example of a Four Alternative, Three Attribute Decision Problem

	Attributes		
Alternatives	Leadership	Creativity	Experience
Weights	6(1)	4(2)	2(3)
A	4(4)	7(5)	4(6)
B	2(7)	7(8)	2(9)
C	6(10)	6(11)	3(12)
D	5(13)	7(14)	2(15)

Table 3

Example of a Three Alternative, Four Attribute Decision Problem

	Attributes			
Alternatives	Leadership	Motivation	Creativity	Experience
Weights	4(1)	5(2)	3(3)	6(4)
Cutoffs	7(5)	4(6)	6(7)	6(8)
A	6(9)	5(10)	7(11)	7(12)
B	7(13)	4(14)	3(15)	6(16)
C	4(17)	3(18)	4(19)	4(20)

Table 4

Intercorrelations Among EIP Counts for the 120 Decision Problems Selected

	Operators				
	ADDITIONS	PRODUCTS	COMPARES	ELIMINATIONS	DIFFERENCES
READS	.487	.543	.541	.280	.272
ADDITIONS		.591	-.259	-.495	.140
PRODUCTS			-.302	-.374	-.146
COMPARES				.852	.492
ELIMINATIONS					.158

Table 5

Summary of Analyses Performed[a]

Dependent Variable	Models			
	Structural	Behavioral	Equal-Weight EIP	Weighted EIP
Response Times				
Overall Decision	X	X	X	X
Individual Acquisition			X	X
Time on Each Alternative		X	X	X
Time on Each Attribute		X	X	X
Index of Subject Effort	X	X	X	X
Errors	X	X	X	X

[a]An X in a cell means that analysis was performed.

Table 6

Summary of Model Fit Statistics

Dependent Variable	Models: Structural	Behavioral	Equal-Weight EIP	Weighted EIP
Response Time[a]				
Overall Decision	.65	.70	.71	.81
Individual Acquisition	---	---	.16	.23
Time for Each Alternative	---	.49	.48	.68
Time for Each Attribute	---	.64	.65	.75
Index of Subjective Effort[b]	.57	.56	.55	.59
Errors[c]	.68	.62	.63	.64

[a]The fit statistics are R^2 values for regressions. The sample sizes were 733, 12178, 2963, and 2313 for the overall decision, individual acquisition, time for each alternative, and time for each attribute models respectively.

[b]The fit statistics are R^2 values for regressions. The sample size was 737.

[c]The fit statistics are pseudo-R^2 values for logistic regressions. The sample size was 840.

: 7

ıates of Time for EIP's (seconds)

: of	EIP					
:gation	READS	ADDITIONS	PRODUCTS	COMPARISONS	ELIMINATIONS	DIFFERENCES
ıll Decision	1.19*	.84*	2.23*	.09	1.80*	.32
;idual Acquisition	--	.57*	1.22*	.17*	.01	.19*
for Each lternative	1.42*	.33*	1.42*	.16*	.10	.28*
for Each :tribute	1.22*	.68*	1.97*	.45*	.26*	.72*

ıificant at $p < .05$.

Table 8

Estimates of Subjective Effort for EIP's

EIP					
READS	ADDITIONS	PRODUCTS	COMPARISONS	ELIMINATIONS	DIFFERENCES
.10*	.08*	.19*	.04	.32*	-.12

*Significant at $p < .05$.

Figure 1

An Example Problem Display

	Leader	Create	Exper
Weights	[redacted]	[redacted]	[redacted]
Cutoffs	[redacted]	[redacted]	[redacted]
Cand A	4 +	[redacted]	[redacted]
Cand B	[redacted]	[redacted]	[redacted]
Cand C	[redacted]	[redacted]	[redacted]
Cand D	[redacted]	[redacted]	[redacted]

Choose one [redacted] [redacted] [redacted] [redacted]

January 1986

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