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# **An Experimental Investigation of the Impact of Computer Based Decision Aids on Decision Making Strategies**

**Peter Todd**

*School of Business  
Queen's University  
Kingston, Ontario  
Canada K7L 3N6*

**Izak Benbasat**

*Faculty of Commerce  
University of British Columbia  
Vancouver, British Columbia  
Canada V6T 1Y8*

Although Decision Support Systems (DSSs) have been in use since the early seventies, there is as yet no strong theoretical base for predicting how a DSS will influence decision making. Furthermore, the findings of various empirical studies on the outcomes of DSS use are often contradictory. Consequently, there is a need in the Decision Support Systems field for theories or explanatory models to formulate hypotheses, to conduct research in a directed, parsimonious manner and to interpret findings in a coherent way. This will assist both academics and practitioners interested in the use of information systems to support managerial workers. This paper proposes the use of a cognitive effort model of decision making to explain decision maker behavior when assisted by a DSS. The central proposition is that specific features can be incorporated within a DSS that will alter the effort required to implement a particular strategy, and thus influence strategy selection by the decision maker. This was investigated in a series of three experimental studies which examined the influence of computer based decision aids on decision making strategies. In the three experiments, subjects were given different degrees of support to deal with various components of cognitive effort (processing effort, memory effort and information tracking effort) associated with the strategies applicable to preferential choice problems. The results show that decision makers tend to adapt their strategy selection to the type of decision aids available in such a way as to reduce effort. These results suggest that the assumption that decision makers use a DSS exclusively to maximize decision quality is open to question. DSS studies which consider the joint effects of effort and quality, or control one while manipulating the other, are more likely to provide consistent and interpretable results.

*Decision support systems—Decision processes—Cognitive cost-benefit theory*

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## 1. Introduction and Objectives

Although Decision Support Systems (DSSs) have been in use since the early seventies, surveys of the field have indicated that there is no strong theoretical base for predicting how a DSS will influence decision making (Benbasat and Nault 1990; Elam, Huber and Hurt 1986; McFarlan 1984, p. 45). Furthermore, the findings of various empirical studies on the effects of DSS use are often contradictory (Benbasat and Nault 1990). There is a need for theories or explanatory models in the DSS field to formulate hypotheses, to conduct research in a directed, parsimonious manner and to interpret findings in a coherent way.

In this paper we employ a cognitive effort perspective of decision making to explain decision maker behavior when assisted with a DSS. The value of this approach is assessed in a series of experiments examining the impact of decision aids on strategy. The cognitive effort perspective provides insight into how DSSs influence the selection of problem solving strategies by altering the effort relationships among the component processes that make up these strategies. It is based on three notions: (1) decomposing decision strategies into their subcomponents could offer estimates of the relative cost of using various strategies (Shugan 1979; Johnson and Payne 1985), (2) these same decompositions can be used to identify the tools required to support a particular strategy (Johnson and Payne 1985), and (3) a DSS can be designed to reduce the cognitive effort required to implement various mental operations that may be subcomponents of one or more strategies by automating storage, retrieval, and computational tasks that the decision maker might otherwise be required to perform (Taylor 1975). Thus, the central proposition of this paper is that specific features can be incorporated within a DSS to alter the effort required to implement a particular strategy, and thus influence strategy selection by the decision maker.

Three experiments were conducted to examine this proposition. In Experiment 1 subjects were assigned to either aided or unaided decision settings and given problems of either five or ten alternatives from which to make a choice. Experiment 2 was similar to Experiment 1 except that subjects were given either 10 or 20 alternatives. The number of alternatives was manipulated to examine the influence of the decision aid under conditions where increased effort was required to use a given strategy. Experiment 3 was designed to examine the effects of different levels of decision support, rather than the availability of an aid, on different components of cognitive effort and strategy selection.

The paper proceeds as follows. In §2 the literature on cognitive effort in decision making is reviewed, the preferential choice task to be employed in the experiments is examined and the strategies commonly studied for such choice tasks are discussed. The strategies are decomposed into a number of mental operations (elementary information processes) and the types of decision support aids required to facilitate their use are described in §3. §4 presents the hypothesis that by altering the relative cost of mental operations associated with the components of different strategies, decision aid use could change the process of decision making. §5 describes the research framework for Experiments 1 and 2. §6 describes their results. §7 presents Experiment 3. §8 provides concluding comments.

## 2. Literature Review

### (a) *The Cognitive Effort Perspective*

Empirical studies of preferential choice indicate that decision makers are highly adaptive in selecting strategies (Johnson and Payne 1985). Researchers have proposed a variety of mechanisms that influence strategy selection (Einhorn and Hogarth 1981). Among these, effort and accuracy have received considerable attention. Payne (1982) proposed a cost-benefit framework of cognition which incorporates the notion that decision makers focus on trade-offs between accuracy and effort in decision making. A subsequent series of both empirical and simulation work undertaken by Payne and his colleagues, among others, is largely supportive of this notion (see, for example, Johnson and Payne 1985; Bettman, Johnson and Payne 1986; Johnson, Payne and Bettman 1988; Payne, Bettman and Johnson 1988; Jarvenpaa 1989; Stone and Schkade 1990; Creyer, Bettman and Payne 1990).

According to the cost-benefit framework, the joint objectives of a decision-maker are to maximize accuracy (or decision quality<sup>1</sup>) and minimize effort.<sup>2</sup> As these objectives often conflict, trade-offs are made between the two. An open question in the current literature is the emphasis or value placed on effort and accuracy in making the trade-off. The traditional DSS literature emphasizes the primacy of decision quality (Keen and Scott Morton 1978). On the other hand, literature in behavioral decision theory indicates that effort may be an important overall consideration in many problem contexts (Kleinmuntz and Schkade 1989; Russo and Doshier 1983). While the trade-off between effort and accuracy is not fully understood and indeed is likely to be highly task dependent, there are two predictions which can be made:

1. Given two strategies which are expected to require the same effort, the one that is expected to produce a more accurate outcome will be preferred, and
2. Given two strategies which produce equivalent outcomes, the one which is expected to require less effort will be preferred.

Conceptual models of decision making have suggested that effort may be the key to explaining much decision behavior. Beach and Mitchell (1978) provide a contingency model which links various personal and task characteristics to strategy selection. They argue that the decision maker is motivated to pursue the least effortful strategy which will provide an acceptable solution, given the various contingencies. Others have also argued that strategies are evaluated in terms of effort, subject to some constraint on decision quality (Shugan 1979; March 1978; and Jungerman 1985). Effort may be weighted more heavily than accuracy because feedback on effort expenditure is relatively immediate while feedback on accuracy is subject to both delay and ambiguity (Einhorn and Hogarth 1978; Kleinmuntz and Schkade 1989).

Monte Carlo simulations of decision strategies demonstrate that heuristics will

<sup>1</sup> Decision quality is usually operationalized as the deviation of a particular solution from the solution that would be provided by a normative strategy, such as expected value maximization or utility maximization.

<sup>2</sup> We would like to acknowledge that there are other theories which can be used to explain the behavior of decision makers within the context of DSS use. For example, Keen and Scott Morton (1978) comment on the implications of organizational and political theories of how managers make decisions for the implementation of DSSs. See also Benbasat and Todd (1991) for other theories of DSS user behavior.

save decision makers considerable effort compared to a normative approach, with little loss of accuracy (Thorngate 1980; Johnson and Payne 1985; Payne et al. 1988). Thorngate (1980) called such heuristics “efficient”. This notion of efficiency provides another reason why effort may have an important influence on strategy selection.

Numerous empirical studies have concluded that decision makers attend more to effort reduction than to accuracy maximization (Russo and Doshier 1983; Christensen-Szalanski 1980; Bettman et al. 1986; Bettman and Kakkar 1977). Johnson et al. (1988) postulate that decision makers may react to display format changes by adopting strategies which minimize effort. Even in the face of significant monetary incentives, effort considerations appeared to have significant influence on strategy selection and, thus, decision quality. Decision makers are more likely to transform strategies to make it easier to work with specific information displays than to transform the information to fit a normative strategy. This is consistent with Slovic’s (1972) notion of concreteness.

Overall, the empirical, simulation and conceptual literatures indicate that effort is an important factor in strategy selection. For DSS researchers, the key message to be taken from this work is that decision makers are not *solely* concerned with decision quality, a factor which has been the main focus of most DSS research to date. Effort considerations can influence the choice of a decision making strategy and as a result decision quality. Decision makers will employ more effortful strategies, which generally lead to higher decision quality, when the DSS reduces the effort needed to use them. By paying careful attention to how a DSS influences effort, it may be possible to predict its effects on strategy selection and decision making. Thus, an *effort perspective* provides a potentially promising approach to understanding the behavior of decision makers using DSSs.

## (b) *Preferential Choice Problems*

(i) *Choice Strategies and Effort*. The focus in this research is on support for preferential choice problems, which are among the generic classes of decision-aiding technologies identified by Zachary (1986). Researchers studying choice problems have commented on the relationship of their work to the design of computer based decision aids, though no formal testing of this relationship has been conducted to date (Johnson and Payne 1985; Kleinmuntz 1987).

Multi-alternative, multi-attribute preferential choice problems deal with tasks where a decision maker chooses one of a number of alternatives, each of which is described by a common set of attributes (Keeney and Raiffa 1976). Svenson (1979) describes 12 strategies applicable to choice problems. Of these, four prototypical decision strategies have been the focus of attention in empirical studies of preferential choice (see, for example, Payne 1976; Olshavsky 1979; Biggs et al. 1985; Sundstrom 1987; Jarvenpaa 1989). They are: additive-compensatory, additive-difference, conjunctive, and elimination by aspects. The characteristics of each strategy are described briefly in Appendix 1. Below we identify the elementary information processes (EIPs) associated with each strategy. An EIP is a basic low level cognitive operation such as reading a value, comparing two values or storing a result in long-term memory. EIPs have been used to model a variety of decision processes (see, for example, Johnson and Payne 1985; Chase 1978).

The Additive-Compensatory (or Additive-Linear) Model (AC) is based on the eval-

TABLE 1  
Effort Required by Each Strategy—Unaided

Additive Strategies		Elimination Strategies		
AC	AD		EBA	CNJ
$c * 7 * r^a$	$(c - 1) * 10 * r$	Number of Alternatives	$r + (r - 1) * c + (r * 4 * c)$	$c + (r * 5 * c)$
280	320	$c = 5$	203	205
560	720	$c = 10$	398	410
1120	1520	$c = 20$	788	820

<sup>a</sup>  $r$  is the number of rows (attributes) and is held constant at 8 for these examples.

uation of one alternative at a time along all relevant attributes. Each attribute is assigned a weight. A score for each alternative is determined by summing the product of the attribute value and the weight. The basic sequence of seven EIPs involved in this process is: **move** to the next attribute, **read** the attribute value, **retrieve** the weight, **combine** the attribute value and weight, **retrieve** the current sum for the alternative, **add** the weighted value to the sum, **store** the new sum. This procedure is iterated for each attribute value describing an alternative. The alternative with the highest final score is chosen.

The total number of EIPs required to implement an AC strategy for a matrix of size  $r * c$ , with  $r$  attributes and  $c$  alternatives, is  $7 * (r * c)$ , with the seven EIPs as listed above being applied to each cell in the matrix. The total number of operations required for 5, 10 and 20 alternative problems with eight attributes is shown in Table 1.

The Additive-Difference model compares attributes for two alternatives at a time (Tversky 1969). For each attribute-pair a difference is taken. The differences are weighted and summed to produce an overall evaluation. Ten EIPs are required: **move** to attribute value  $a$ , **read**  $a$ , **move** to attribute value  $b$ , **read**  $b$ , **subtract**  $a$  from  $b$  giving difference  $d$ , **retrieve** weight, **combine** difference  $d$  and weight, **retrieve** the overall score, **add** weighted difference to overall score, **store** total difference. When the comparison for a pair of alternatives is complete, the preferred alternative is retained while the other is rejected. The retained alternative is then compared against the next alternative. This process is repeated until one alternative remains (i.e.,  $c - 1$  times for  $c$  alternatives).

The total number of EIPs required to implement an AD strategy for an  $r * c$  matrix is  $(10 * r) * (c - 1)$ . The constant 10 represents the 10 EIPs that were outlined above for each pairwise comparison. The total number of operations required for different numbers of alternatives is shown in Table 1.

The conjunctive (CNJ) model is based on the evaluation of each attribute against a minimum threshold level. The basic sequence of EIPs is: **move** to new attribute, **read** attribute value, **retrieve** threshold value, **compare** attribute value and threshold, and **eliminate** the alternative if threshold is violated. Information is examined by alternative; if an alternative violates a specified threshold for any of the attributes it is dropped from further consideration. As the search progresses, indicators of acceptable alternatives are stored in memory. If there is more than one acceptable alterna-

tive the thresholds are redefined. The search is then repeated using the more restrictive thresholds. This procedure is repeated until only one alternative remains.<sup>3</sup>

The total number of EIPs required to implement a CNJ strategy for an  $r \times c$  matrix is  $5 \times (r \times c) + c$ ; the constant 5 represents the 5 EIPs that were outlined above for each pairwise comparison and  $c$  is the maximum number of operations required to store the labels of acceptable alternatives. The total number of operations required for different numbers of alternatives is shown in Table 1. These EIP estimates assume that all information in the problem set is examined prior to choice. Because CNJ is, in fact, a filtering strategy in which some information is virtually always ignored, it should be pointed out that these estimates represent upper bounds on the effort required for the strategy.

The Elimination by Aspects (EBA) model was first formalized by Tversky (1972). As with the CNJ model, attribute values are compared against some threshold level. However, in the EBA model, values for an attribute are examined across all alternatives. The sequence of EIPs is essentially the same as for CNJ: **move**, **read**, **compare**, and **eliminate**. However, thresholds are **retrieved** only once per attribute, rather than once per cell. Any alternative which does not meet the threshold level for any attribute is eliminated. All remaining alternatives are evaluated against the next attribute. This procedure is repeated until a single alternative remains.

The attribute based comparisons also require the decision maker to keep track of the status of each alternative (i.e., eliminated or still being considered). Before each alternative can be evaluated on a specific attribute, it is necessary to **retrieve** a status indicator which shows whether that alternative is still under consideration or has been previously rejected.

The total number of EIPs required to implement an EBA strategy for an  $r \times c$  matrix is  $r + (r - 1) \times c + 4 \times (r \times c)$ . The factor  $r$  represents the memory retrievals for the attribute threshold values, and the constant 4 represents the 4 EIPs that were outlined above for each comparison of a cell value to threshold. The factor  $(r - 1) \times c$  represents the number of operations required to track the status of alternatives in the matrix. This tracking process does not take place when the first attribute is examined since all alternatives are still available at that time, thus the  $c$  comparisons are repeated  $r - 1$  times. The total number of operations required for different numbers of alternatives is shown in Table 1. As with CNJ these estimates assume complete search and thus represent upper bounds on effort. The required number of operators cannot be determined *a priori* because of the impact of task characteristics on the amount of information searched. Below we take a closer look at the effort required for EBA and CNJ in the context of information elimination.

In the analysis above we assumed that different EIPs require equivalent cognitive effort. While this is an obvious simplification, simulation studies have shown that models of simple decision strategies lead to estimates of equivalent effort regardless of whether the individual EIPs are weighted differently or equally (Johnson and Payne 1985). Our analysis also assumes that because immediate processing occupies short-term memory, status indicator and threshold values will be retrieved from long-term

<sup>3</sup> It should be noted that this stopping rule is different from the typical satisficing rule that is commonly applied to CNJ. Under a satisficing rule search stops when a single acceptable alternative is found. The stopping rule we define makes EBA and CNJ more directly comparable and is consistent with the behavior of subjects we have observed for this type of task.

TABLE 2  
EBA versus CNJ. The Components of Effort

Elimination by Aspects				Conjunctive		
Memory	Tracking	Processing		Memory	Tracking	Processing
Part A			Number of			
$r^a$	$((r - 1) * c)$	$r * (4 * c)$	Alternatives	$r * c$	$t$	$r * (4 * c)$
8	35	160	$c = 5$	40	5	160
8	70	320	$c = 10$	80	10	320
8	140	640	$c = 20$	160	20	640
Part B			Number of			
$r$	$((r - 1) * c)$	$4 * \sum_{i=0}^{r-1} (c - (i * (c/r)))$	Alternatives	$((r + 1)/2) * c$	$t$	$4 * ((r + 1)/2) * c$
8	35	60	$c = 5$	22.5	1	90
8	70	180	$c = 10$	45	1	180
8	140	360	$c = 20$	90	1	360

<sup>a</sup>  $r$  is the number of rows (attributes) and is held constant at 8 for these examples.

memory. In this respect, our models represent maximum levels of effort expenditures to follow a particular strategy. To the extent that some of the status and threshold values can be held in short-term memory the effort required would be reduced.

The additive strategies (AD and AC) require more effort than the elimination strategies (EBA and CNJ), even under the assumption that the whole matrix will be examined for each strategy (Table 1). This evaluation is consistent with previous research which has demonstrated that decision makers are more likely to use strategies such as EBA and CNJ under conditions of moderate cognitive load (Payne 1976; Olshavsky 1979). Consequently, the first two experiments focus on the elimination strategies to test the proposition that strategy is influenced by changes in effort due to DSS use. Since EBA and CNJ are the naturally employed strategies, providing support for them is in line with the DSS philosophy of user control (Silver 1990). The objective was to keep the systems and the interface as simple as possible at this early stage of research. In the third experiment this constraint is relaxed: a support tool designed to assist with AD is tested.

(ii) *A Closer Look at Effort for EBA and CNJ.* Table 2 shows the breakdown of effort required to execute the two elimination strategies for different numbers of alternatives. The effort expenditures have been broken down into: (1) a memory component, which accounts for the retrieval of threshold values, (2) status information for tracking acceptable and unacceptable alternatives, and (3) a processing component for the comparison of attribute values to thresholds. Part A of Table 2 shows the number of processes that would be required for problems with 5, 10 and 20 alternatives, assuming that it would be necessary to examine all available information prior to arriving at a choice. These estimates are reasonable upper limits on effort.

The effort required for EBA and CNJ is similar. The processing effort is  $r * (4 * c)$

units in each case. The memory requirements differ. CNJ requires a greater number of memory retrievals to obtain threshold values;  $r * c$  for CNJ versus  $r$  for EBA. EBA, however, has a more substantial tracking requirement. The decision maker must track whether a particular alternative is still included in the feasible set. After the first value is examined this value will be checked once each time an attribute value is accessed; hence it requires  $(r - 1) * c$  operations. For CNJ it is only necessary to record the acceptable alternatives. This would require at most  $c$  operations, assuming all alternatives are acceptable. Thus a decision on whether to adopt EBA or CNJ could be based, in part, on differences in the assessment of the effort required for tracking requirements versus memory requirements. Tracking may be more difficult because the information is new to the decision maker, while the swaps of threshold values are based on retrievals from memory of previously developed preferences.

Since both EBA and CNJ are elimination strategies, some information is likely to be ignored. This is borne out by previous studies (e.g., Payne 1976). However, estimating the total number of EIPs utilized is difficult since factors, such as location and number of acceptable alternatives, as well as the number of unacceptable attribute values and their location, will affect the amount of effort taken to make a choice. Part B of Table 2 shows the number of operators required under certain more restrictive assumptions, namely:

- (i) there is only **one** acceptable alternative which is randomly located in the choice set,
- (ii) all other alternatives are unacceptable on only **one** attribute, which is randomly located among the  $r$  attributes.

This example is only meant to **illustrate** the relative levels of effort required for EBA and CNJ under this particular set of assumptions. The assumption of one acceptable alternative means that there is a personal "best" choice for each decision maker. The assumption that there is only one unacceptable attribute in each alternative simply means that decision makers will examine, on average, half of the information about an alternative prior to its elimination. Having a greater number of undesirable alternatives or undesirable attributes would reduce the search space for both EBA and CNJ. Assuming that both strategies are carried through until a single alternative remains, it should not have a differential impact on the amount of effort required for each strategy.

The expected search space for CNJ under these conditions becomes  $(r + 1)/2$ , since the unacceptable attribute is randomly placed with equal probability in any cell for each alternative. The decision maker will only need to track the one acceptable alternative, thus the tracking component requires only one operation. The memory and processing components of CNJ are reduced from a total of  $5 * r * c$  when the full matrix is searched to  $5 * ((r + 1)/2) * c$ .

For EBA the assumptions made above can be approximated by uniformly reducing the number of alternatives with each attribute search until only one alternative remains. This implies that for the five-alternative case, one alternative is eliminated each time an attribute is scanned, for the ten-alternative case, on average, 1.25 alternatives are eliminated and for the 20-alternative case 2.5 alternatives are eliminated. The total effort is calculated as:  $4 * \sum_{i=0}^{r-1} (c - (i * (c/r)))$ .

Based on the preceding analysis, EBA and CNJ require approximately the same amount of total processing effort for a decision maker facing an attribute by alterna-



	A	B	C	D	E	F	G	H	I	J
Noise										
Brightness										
Rent										
Bedrooms										
Size										
Laundry										
Distance										
Cleanliness										

FIGURE 1. The Attribute by Alternative Matrix Displayed to Subjects (10 Alternatives)

tive matrix. In the next section we will discuss how a decision aid which affects the different components of effort, shown in Table 2 will influence strategy selection.

### 3. The Decision Aid

Johnson and Payne (1985) have proposed that understanding the underlying components of a decision strategy will assist in building systems to support particular decision tasks. The approach taken to building the DSS for this study followed this philosophy. The actual development process is described in Appendix 2. The general strategy descriptions provided above were developed into formal models of the strategies. These formal models (discussed in detail in Todd 1990) describe the basic EIPs that are required for each strategy. Decision aids can be constructed to automate one or more EIPs that the decision maker would use in a particular strategy. The decision aid does not restrict the behaviour of users by guiding them through a series of operations. Rather users could choose individual commands and combine them as they saw fit. Thus, the DSS is not highly restrictive in the sense discussed by Silver (1990).

In using the decision aid, subjects are presented with an attribute by alternative matrix for an apartment selection problem on a computer display terminal (see Figure 1). Initially the matrix is blank. Subjects access information by opening rows (attributes), columns (alternatives) or individual cells. A subject with no decision aid has access only to the (unconditional) OPEN command used to uncover any cell, row or column of the matrix. A subject with the decision aid has a wide range of commands available for accessing and manipulating information (see Table 3).

Although the commands built into the decision aid could be used to support both EBA and CNJ, it is clear that the system provides the greatest support for EBA. The CONDITIONAL DROP command automates the **move/read/compare/eliminate** sequence of operations associated with EBA, automatically comparing attribute values to a specified threshold and eliminating any alternatives which violate the threshold. All that is left for the user to do is retrieve threshold values (i.e.,  $r$  operations as

TABLE 3  
Decision Aid Command Descriptions

COMMAND	DESCRIPTION
OPEN	unmasks a specified <b>cell, row (attribute) or column (alternative)</b> .
CLOSE	masks a specified <b>cell, row or column</b> that has been previously opened.
CONDITIONAL OPEN/CLOSE	opens or closes <b>cells in a row</b> contingent upon the value of an attribute. Compound conditions are not permitted. Available operators are >, < or =.
DROP	causes a specified <b>row or column</b> to be deleted from the matrix.
CONDITIONAL DROP	drops <b>columns</b> contingent upon the value of an attribute.
SORT	sorts <b>columns</b> in ascending or descending order according to a specified <b>attribute</b> key or multiple keys.
MOVE	places any two specified <b>rows or columns</b> side-by-side in the matrix.
REORDER	allows any number of <b>rows or columns</b> to be rearranged into a specified order.
CALCULATE	creates a <b>new attribute</b> which is any mathematical combination (+, -, *, /) of <b>two existing attributes</b> . The existing attributes remain unchanged.
RESTORE	causes all <b>previously deleted (dropped) rows or columns</b> to be placed back in the matrix.

shown in Table 2) and enter them into a CONDITIONAL DROP command. The processing steps (shown in Table 2) are all handled by this command. In addition, since undesirable alternatives are automatically eliminated, the memory load associated with determining the status of an alternative is also eliminated. In this way the CONDITIONAL DROP supports both processing and memory. Note that CONDITIONAL CLOSE which masks, but does not eliminate, violated alternatives from the matrix has the same effect as the CONDITIONAL DROP.

SORT could also be used to support EBA. By sorting on a particular attribute, from best to worst, a serial search of alternatives could quickly be made to identify those alternatives which violate a specified threshold. Given a sorted series of values, once a single value violating the threshold has been discovered, the user would know that all subsequent values would also violate the threshold. A DROP command could then be employed to eliminate the remaining unacceptable alternatives. The direct savings using this approach depends upon the number of acceptable alternatives in the choice set. Assuming that only one quarter of the remaining alternatives are eliminated with each repeated use of the SORT/DROP combination, approximately half of the EIPs required for an equivalent manual search would be saved.

The CLOSE and DROP commands are used to manage the presentation of information. By dropping or closing the rejected alternative the decision maker would save the operations associated with retrieving indicator values to determine the status of each alternative. These commands also facilitate reading specific information since having extraneous information displayed increases the possibility of error in locating and reading the correct values.

The system does not provide the same level of support for CNJ as it does for EBA. While closing or dropping alternatives may alleviate some of the effort of locating and reading correct values, it does not relieve the memory burden of the threshold retrievals. Computational processing support is also minimal. While the use of SORT could bring promising alternatives to the beginning of the matrix, possibly leading to the early discovery of a solution, it does not provide an equivalent level of support to that provided by CONDITIONAL DROP for EBA.

#### 4. Hypothesis Development

Our basic proposition is that, **all other things being equal, if a decision support system reduces the effort associated with employing a particular strategy relative to other strategies, a decision maker will be more inclined to employ that strategy.** The hypotheses to be tested are:

**H1. The aided decision makers will search by attributes while the unaided decision makers will search by alternatives.**

**H2. The aided decision makers will follow an EBA strategy while the unaided decision makers will follow a CNJ strategy.**

As discussed in the previous section, the decision aid creates an effort gap between CNJ and EBA. The two strategies require approximately the same amount of total effort for an unaided decision maker given a matrix presentation for displaying attributes and alternatives (see Figure 1). With the decision aid, EBA becomes less effortful and should be the preferred strategy. It provides a significant savings which reduces both processing and memory load. By contrast, using the decision aid to implement a CNJ search would require that the decision makers themselves **move, read and compare** values as there is no command to do this automatically. Even if the CONDITIONAL DROP is not used, commands such as SORT, DROP and CLOSE should provide sufficient effort reduction incentive for aided decision makers to use EBA.

For the type of selection task used in this research, **unaided** subjects have been observed to use primarily EBA and CNJ strategies (Payne 1976; Olshavsky 1979; Biggs et al. 1985; Sundstrom 1987). As discussed previously, when following an EBA strategy the decision maker has **many alternatives under consideration at the same time** and must remember which alternatives have and have not been eliminated. Otherwise, needless reprocessing may occur when the next attribute is examined, as attribute values of previously eliminated alternatives are reconsidered. More importantly, **there is an increased chance of making an error in the final choice.** The decision maker may forget that an alternative has been eliminated and reenter it into the choice process, or conversely may forget to consider a viable alternative.

With CNJ, each alternative is processed sequentially and thus errors of this type are less likely to occur. Only status indicators of **acceptable** alternatives must be stored. In addition, it may be less effortful for the decision maker to retrieve threshold values already stored in memory than to store and retrieve status indicators as required by EBA. Given two strategies that require **approximately** the same effort, it is reasonable to assume that the decision maker will choose the one that offers greater potential accuracy. Thus, we expect that those in the unaided group will use CNJ.

In Experiments 1 and 2, both problem size and the availability of the decision aid are manipulated. As problem size increases, the gap between EBA and CNJ increases because of the availability of the CONDITIONAL DROP for EBA. The use of CON-

DITIONAL DROP requires the same amount of effort regardless of the number of alternatives in the choice set, while the number of cognitive operations it replaces increases with the number of alternatives. Thus, as problem size increases the tendency of aided decision makers to use EBA and search by attribute should be reinforced.

For the unaided decision maker the chance of making an error when using EBA would increase as the number of alternatives increases. As a consequence, the problem of tracking acceptable alternatives also increases. Thus, an increase in problem size would also reinforce the tendency of the unaided decision maker to use CNJ. Based on this reasoning we expect:

**H3. As problem size increases, the aided decision makers will more likely search by attributes while the unaided decision makers will more likely search by alternatives.**

**H4. As problem size increases, the aided decision makers will more likely use EBA while the unaided decision makers will more likely use CNJ.**

## 5. Framework for Experiments 1 and 2

The experimental design and procedures for Experiments 1 and 2 (E1 and E2) are both described in this section since they are very similar. The findings of the two experiments are then presented in §6.

### (a) *The Independent Variables*

The experiments investigated two factors, each at two levels. The primary factor was the presence or absence of a decision aid. The second factor was the number of alternatives from which a choice was to be made.

(i) *The Decision Aid.* The decision aid contained a set of commands outlined in Table 3. Aided decision makers could use any of these commands to support the choice process. Interaction took place by entering commands at a prompt line. The commands consisted of a Command Name (see Table 3) and parameters to indicate rows, columns or threshold values against which to apply the command. For example, to sort all values of rent (stored in row 3 of the matrix) in ascending order the user would enter SORT 3 A (where A is the abbreviation for ascending). To drop alternative H, the user would enter DROP H.

Unaided decision makers could only use the system to access data (via the OPEN command); no processing or data manipulation capabilities were provided.

(ii) *Problem Size.* The number of attributes describing each alternative was held constant at eight. Eight is the mean number of attributes used by Payne (1976). Subsequent research of this type has used seven attributes (Biggs et al. 1985; Jarvenpaa 1989). Overall, the number of alternatives has been more influential on strategy than has the number of attributes (Malhotra 1984; Jacoby 1984; Stone and Schkade 1989).

The number of alternatives was manipulated to investigate the value of the decision aid under differing levels of information load. Certain commands, such as CONDITIONAL DROP and SORT (see Table 3), apply across all alternatives in the choice set and hence replace multiple cognitive operations. The effort to use each of these functions does not change as a function of problem size, yet the benefits in terms of cognitive effort saved increases. As a result, the marginal difference between

the cost of using the decision aid and the benefits it provides in terms of reducing cognitive effort increases with problem size. Based upon this reasoning, the value of a decision aid may depend on the size of the choice problem. Thus, problem size was manipulated at 5 and 10 alternatives for E1, and at 10 and 20 alternatives for E2. This permits us to examine the influence of the decision aid under increasing levels of cognitive load.

### (b) *The Dependent Variables*

Strategy is measured in two ways. The first is “**direction of search**” which can be by attribute, by alternative or some combination of the two. Direction of search is an important determinant of strategy in preferential choice and has been employed previously by Payne (1976), Biggs et al. (1985), Johnson et al. (1988) and Jarvenpaa (1989). For this study it is defined as:

$$\frac{\text{Number of “Attribute” Runs} - \text{Number of “Alternative” Runs}}{\text{Total Number of Runs}} * 100.$$

A “run” is any reference in the verbal protocol to two or more consecutive attributes or alternatives. For example, if a subject looks at all values across the attribute “noise”, that would count as one attribute run. Examining any sequence of attributes such as rent, size, and distance, for one alternative, counts as one alternative run. Values can range from -100 to +100. +100 implies a pure attribute based search indicative of AD and EBA. -100 implies a pure alternative based search indicative of CNJ and AC.

A run is used as the basic unit of analysis since the strategies focus on evaluations of alternatives or attributes. When the number of attributes and alternatives are not equal, the number of pairwise transitions can take on different meanings. If, for example, a subject first examined all values for rent in a 20-alternative problem, that would be considered one run but 20 pairwise transitions. If the decision maker then looked at three alternatives in detail, the pairwise count would yield 24 transitions ( $8 * 3$ ), while the run score would be three. Overall the pairwise analysis would indicate a neutral search pattern ( $(20-24)/44$ ) while the run score would indicate a tendency towards alternative based processing ( $((1-3)/4)$ ). We believe this latter measure better reflects the behavior of subjects and takes into account that the major focus of the strategies is on attributes or alternatives and not simply pairs of values.

The protocols were coded to determine an **overall strategy** assignment, based upon a scheme developed by Biggs (1978). The criteria for strategy classification are shown in Appendix 1. The coding rules are shown in Appendix 3. Strategies are classified as either AC, AD, CNJ, EBA or as indeterminate. The classification is made by evaluating the six criteria and determining the fit of each strategy against the six criteria. Thus, a score from zero to six is available in each case. The strategy which best conforms to the criteria and corresponds to at least five of the six criteria is selected. If less than five criteria match any strategy, then no determination is made and that observation is left out of the analysis. Similarly if there is a tie, with two strategies being equally likely, the strategy is considered indeterminate. This procedure has been demonstrated to be reliable by Biggs et al. (1985) and Jarvenpaa (1989).

### (c) *Task Environment*

Subjects performed an apartment selection task similar to that employed by Payne (1976). This task was chosen because: (1) it is a common choice problem for which a

large proportion of the subject population (university students) have had previous experience, (2) the task requires no specialized knowledge, and (3) observations during pilot testing indicated that subjects could relate easily to this problem.

The eight attributes used were: rent, size, number of bedrooms, noise, brightness, laundry, cleanliness, and distance to campus. The data for the problem relating to rent, number of bedrooms, size, laundry and distance to the university were taken from advertisements in local newspapers. This helped to ensure that the choices approximately mirrored those available in the local market. Where possible, data were reported in the appropriate metric (for example, rent in dollars per month). Noise, brightness and cleanliness ratings were provided on a five-point ordinal numeric scale. These values were assigned at random. Laundry was represented by a binary (yes/no) value. Although there is evidence that data format (e.g. numeric versus text) can affect processing (Stone and Schkade 1989), this was not tested in this study; all treatment groups received identical attribute presentations. Information for each attribute was presented as a row in the matrix (see Figure 1). Ordering of the rows and columns was determined randomly prior to the experiment.

Each alternative had both good and poorly valued attributes. No alternative was either superior to or inferior to any other alternative along all attributes. In E1, all alternatives used in the five-alternative setting could be found in the ten-alternative problem set. In E2 all alternatives used in the ten-alternative problem set could be found in the 20-alternative set. In addition, no data were repeated between the practice session and actual experimental task.

#### (d) *Subjects*

All subjects for E1 and E2 were undergraduate business students. Participation was strictly voluntary. Monetary incentives of \$50, 40, 30, 20, and 10 were awarded, at random, to five subjects after the experiment was completed.

Twenty-eight subjects participated in E1, of whom 15 were female. There were also 28 subjects in E2 of whom 14 were female. None of the subjects for E1 were included in E2. For each experiment seven subjects were assigned at random to each of the four combinations of decision aid and problem size.

#### (e) *Experimental Procedures*

Subjects were run through the study one at a time. Each subject went through three steps: (1) tutorial, (2) practice session, and (3) experimental session. First, a **tutorial** was provided to explain each of the commands and enable subjects to perform various tasks which required the use of all the commands. The tutorial did not make any direct linkages between the commands and various choice strategies. Further, the tutorial was based upon a “dummy” problem of selecting alternative widgets, each described by a set of meaningless attribute names. Its purpose was to familiarize subjects with the way the commands functioned. Since the unaided group subjects received only the OPEN command, their tutorial focused only on how to open rows, columns and cells. During the tutorial a lab assistant was present to answer any questions that subjects had about the decision aid.

Following the tutorial, subjects were taken first through a **practice session** and then the **experimental session**. Both dealt with apartment selection problems; the attributes of the choice set were the same but different data were used. While making a choice the subjects were asked to think out loud. The practice problem was intended to give the subjects a chance to familiarize themselves with the task setting, gain

further experience with command use, and become comfortable with verbalizing. Instructions were provided to the subjects on how to verbalize, following the recommendations of Russo et al. (1986).

No time constraints were imposed. Subjects were free to use as much or as little information as they wished. The aided group subjects were told to use whatever commands they thought were appropriate. Subjects were to treat the problem as if they were making a selection for themselves.

During both the experimental and practice sessions a lab assistant was present, though out of sight of the subjects. The lab assistant would prompt subjects to "please say what you are thinking" if they were silent for more than 10 seconds. While engaged in the choice process, an audio tape was made of each subject's verbalization. Subjects were aware that they were being recorded. A computer log unobtrusively captured all key strokes and recorded time spent on the task. The data used in the following analyses were the ones collected during the experimental session.

#### (f) *Summary of Differences Between Experiments 1 and 2*

E1 investigated the influence of the decision aid for choice problems with 5 and 10 alternatives. This problem size has been studied previously in the choice literature; thus, E1 serves as a point of comparison to earlier work which did not study decision aids. E2 examines the influence of the decision aid for problems with 10 and 20 alternatives.

The decision aid used in E2 was identical to that used in E1, although presentation of information differed. Since it was not possible to display 20 alternatives on a single display screen, the display was provided via two 10-alternative screens. To ensure a balanced comparison, the 10-alternative treatment for E2 was presented on two 5-alternative screens (the same display used by the 5-alternative group subjects in E1). Thus, subjects in the 10-alternative treatment could see any five consecutive alternatives on the screen at one time, while those in the 20-alternative treatment could see ten consecutive alternatives at a time. Subjects scrolled across the two screens using cursor keys. In summary, the screen sizes used were:

E1 (5 alternatives):	one, 8*5 display,
E1 (10 alternatives):	one, 8*10 display,
E2 (10 alternatives):	two, 8*5 displays,
E2 (20 alternatives):	two, 8*10 displays.

Cumulatively, these changes in E2 increase the cognitive load on subjects by placing greater demands on memory and, in the 20-alternative setting, increasing information load. Other than these differences, E2 was identical to E1 in terms of design, experimental procedures, task, and dependent variables measured.

## 6. Presentation of Findings for Experiments 1 and 2

### (a) *Analysis of Data*

The statistical model analyzed the main and interaction effects of problem size and decision aid for the dependent variable "direction of search" using  $2 \times 3$  between subjects factorial design (SAS 1985). The strategy measure was evaluated using the Categorical Modelling procedure (CATMOD) in SAS (1985). This procedure, which permits hypothesis testing for nominal data, is an extension of the ANOVA approach. The data analysis reported is for the pooled sample of data from E1 and E2.

Pooling the two samples was possible because the two studies were similar in all

TABLE 4  
ANOVA Results-Direction of Search (Experiments 1 & 2)

SOURCE	DF	F-value	P Value		5 alts	10 alts	20 alts	
DECISION AID	1	23.37	0.0001	No Aid	-18 (72) <sup>a</sup>	-23 (44)	-77 (21)	-35
PROBLEM SIZE	2	1.31	0.28					
AID*SIZE	2	3.68	0.03	Aided	-2 (76)	48 (61)	52 (44)	37
					-10	13	-12	

<sup>a</sup> Mean Score (Standard deviation): -100 = pure alternative search, +100 = pure attribute search.

respects except screen size. Tests of the impact of the screen effect for the 10-alternative one- and two-screen cases, from E1 and E2 respectively, indicated that there was no effect due to screen sizes on the dependent variables. The pooled sample facilitates testing of the interaction effects between problem size and decision aid, and increases statistical power.

Prior to analysis, reliability of the protocol coding scheme was tested. All protocols were coded by the first author. Sixteen protocols, representing approximately 1000 coded statements, were then selected at random and coded by a second person. The second coder was given a written description of the coding rules and these were reviewed with the authors. The raw proportion of agreement between the two coders was 0.82; the value for Kappa, which represents raw agreement adjusted for chance (Cohen 1960) was 0.74. In addition, the coding scheme has been employed and shown to be reliable in previous research (Biggs et al. 1985; Jarvenpaa 1989). Analysis is based upon the coding of the first author.

#### (b) Results for E1 and E2

The mean values for the treatments and the significance levels for the hypothesis tests are shown in Tables 4, 5 and 6. The findings are as follows:

TABLE 5  
Categorical Modeling Results-Strategy (Experiments 1 & 2)

SOURCE	DF	CHI-SQUARE	PROBABILITY
DECISION AID	1	23.71	0.0001
PROBLEM SIZE	2	5.10	0.078
AID*SIZE	2	6.12	0.046

  

	5 alternatives		10 alternatives		20 alternatives	
	Elimination By Aspects	Conjunctive	Elimination By Aspects	Conjunctive	Elimination By Aspects	Conjunctive
No Aid	3 <sup>a</sup>	2	3	9	0	6
Aided	4	2	9	0	6	1

<sup>a</sup> Number of subjects using the specified strategy.



TABLE 6  
*Independence between Decision Aid and Strategy for Different Problem Sizes*

	5	Alternatives 10	20
Chi-Square Test	0.05 <sup>a</sup> $p = \text{NS}^b$	11.8 $p = 0.001$	9.55 $p = 0.002$
Fisher's Exact Test	$p = \text{NS}$	$p = 0.001$	$p = 0.005$

<sup>a</sup> Chi<sup>2</sup> value

<sup>b</sup> NS =  $p > 0.05$ .

**H1/H3: Direction of Search**—Direction of search was significantly different for the aided and unaided subjects ( $p = 0.0001$ ) (see Table 4). Unaided subjects searched by alternatives (direction of search score =  $-35$ ), aided subjects searched by attributes (score =  $+37$ ).

The aid by size interaction effect was also significant ( $p = 0.03$ ). As the problem size increases, the score of the unaided group comes closer to that of a pure alternative search (from  $-18$  to  $-77$ ) while the aided group moves more towards an attribute search ( $-2$  to  $+52$ ). A Scheffé test indicates that the interaction term is attributable to the increase in difference between aided and unaided subjects for the 20 alternative groups. As the number of alternatives becomes larger, the tendency towards attribute based search for the aided group and alternative based search for the unaided group becomes more pronounced.

**H2/H4: Strategy**—The use of the decision aid significantly influenced the type of strategy employed ( $p = 0.0001$ ) (see Table 5). Nineteen of 24 subjects with the decision aid, for whom strategies could be identified, used EBA, while three used CNJ. In contrast, for the unaided group 17 out of 23 subjects used CNJ and six used EBA.<sup>4</sup>

The aid by size interaction effect was also significant ( $p < 0.05$ ). The data in Table 5 indicate that for larger problem sizes, (i.e., 10 and 20 alternatives), differences in strategy become more pronounced than for the five-alternative case. Statistical tests of independence for each of the three problem sizes are shown in Table 6.<sup>5</sup> The test values indicate that for the five-alternative problem, decision aid use does not influence strategy. For the 10- and 20-alternative problems decision aid use has a significant influence on strategy selection.

### (c) *Discussion of Experiments 1 and 2*

The findings of E1 and E2 indicate decision maker adaptability to problem size and to the tools available for reducing cognitive effort. The important areas of effort expenditure are processing, memory and attention focusing. The manner in which the decision aid influences these three types of effort explains why the EBA strategy was used by subjects with the decision aid.

First, consider **processing effort**. Of the 28 subjects with the decision aid in E1 and E2, 12 used the **CONDITIONAL DROP** command (4 times each on average). Sub-

<sup>4</sup> Nine observations of strategy are excluded from this analysis. Three were classified by the coding scheme as using additive strategies, the remaining six could not be classified based upon the evidence available.

<sup>5</sup> In all cases, because of the small cell sizes, Fisher's exact test was used in addition to the Chi-square. Conclusions derived from both tests were always consistent.

jects employing the **CONDITIONAL DROP** saved the associated processing and tracking effort. For the 16 subjects who did not use **CONDITIONAL DROP** other effort considerations are important.

With the decision aid **memory load** favors the use of EBA over CNJ. Since CNJ processing is alternative based, the threshold values must be swapped into short-term memory as **each cell** of an alternative is considered. By contrast, using EBA, one pass through the entire problem would require only  $r$  retrievals and the status of alternatives is managed by use of **DROP** or **CLOSE** commands which were used a total of 147 times by 24 subjects, an average of approximately six times per session. This reduces the memory load for EBA. Short-term memory demands are often cited as a major bottleneck in information processing (Miller 1956).

Taken together, the processing advantage, relief from the burden of attention focusing, and minimization of memory demands make the use of EBA very attractive for the aided group subjects. For the unaided group, CNJ processing can be justified by the trade-off between effort and accuracy. As indicated previously for the unaided subject CNJ is likely to be less error prone. It can also be argued that the threshold swaps associated with CNJ are less effortful than the storage and retrieval of status indicators required for EBA. Further, if it is possible for decision makers to store the threshold values in short-term memory during processing then CNJ becomes even less effortful for the unaided decision maker.

To summarize, the decision aid influenced strategy selection in the way a cognitive effort saving perspective would predict. These results show that effort based explanations are a fruitful approach to understanding the impact of a decision aid on strategy and behavior. Developing a decision aid which changed the relative effort required to use one of two elimination strategies led decision makers to select that strategy in making a choice, even though without the aid they were more likely to employ the other strategy.

The transition from CNJ to EBA was based on simplifying strategies that belong to the same class of elimination approaches. Ideally, a decision aid should provide an incentive for a user to employ strategies that would not be used because they are too effortful but which would be desirable in the sense of providing greater accuracy. The possibility of this is examined in Experiment 3, where support is provided for both elimination and additive strategies.

### 7. Experiment 3

The features included in the decision aid in E3 were manipulated to provide different levels of support for EBA and AD strategies. Based upon this, it was possible to assess the extent to which decision makers adapt their strategies to particular tools which replace different types of effort. For both EBA and AD, high and low support conditions were created. High and low are not intended to specify any absolute level of support. Rather they indicate that more effort would be required in the low support condition than in the high support condition to utilize the specified strategy.

#### (a) *Support for Additive Difference*

Support for AD was manipulated because an analysis of protocols from E1 and E2 indicated that almost all subjects converged on AD towards the end of the choice process. Although our overall evaluation of strategy indicates EBA and CNJ were the dominant strategies used, most processing towards the end of a choice problem involved the comparison of alternatives. Such behavior has been noted previously by

PREFERENCE	BETTER ALTERNATIVE	DIFFERENCE		A	B
QUIETER	B	3	NOISE	4	1
BRIGHTER	B	3	BRIGHTNESS	4	1
CHEAPER	B	45	RENT	400	355
MORE	-	0	BEDROOMS	1	1
BIGGER	A	100	SIZE	650	550
YES	A	YES	LAUNDRY	YES	NO
CLOSER	B	2	DISTANCE	8	6
CLEANER	A	3	CLEANLINESS	1	4

FIGURE 2. A Sample Table Generated by the Compare Function.

Olshavsky (1979) and Bettman and Park (1980), AD has seldom been noted as an overall choice strategy in multialternative settings. We suspect that **AD may be a generally desirable strategy, but one which requires too much cognitive effort in all but the simplest problem settings.** By providing support for the processing associated with AD it may be possible to induce decision makers to use it.

High support for AD was provided by the introduction of a COMPARE function. This function takes differences between any pair of alternatives, indicates the preferred alternative for each attribute<sup>6</sup> and displays the magnitude of the difference between alternatives (see Figure 2). The COMPARE function assumed monotonic preferences on the part of users. Counting the number of attributes for which alternative *X* is superior to alternative *Y* provides direct support for a "majority of confirming dimensions" strategy (MCD). This is an equal weight form of AD (Russo and Doshier 1983).

#### (b) *Support for EBA*

Support for EBA was manipulated because it was the strategy used by aided decision makers in E1 and E2. Manipulation of EBA support should help to uncover the extent to which processing versus memory and attention issues are important in determining strategy.

The manipulation of support for EBA was provided through the inclusion and exclusion of the CONDITIONAL DROP command which provides processing support for EBA. With the exception of these manipulations, the features contained in the E3 decision aid were identical to those used in E1 and E2.

#### (c) *Hypothesis Development*

The hypotheses for E3 reflect how a decision maker might respond to changes in **relative effort** required to pursue different strategies. The dependent variables in this study are identical to those used in E1 and E2 with the addition of **a measure of the degree of AD processing; the dependent evaluation.** A dependent evaluation is defined as: **a pairwise comparison between two alternatives for a single attribute.** For

<sup>6</sup> Subjects expressed the direction of their preferences for each attribute prior to the experiment. All subjects were consistent with each other in their specification of preferences for each attribute. For example, all subjects preferred apartments which were lighter to darker, bigger to smaller, cheaper to more expensive, and so on.

example, a statement such as “apartment A is noisier than apartment B” is a dependent evaluation. AD is the only strategy which employs such comparisons.

(i) *Additive Difference Support Hypotheses.* COMPARE eliminates half of the computations associated with AD, namely the series of five operations (**move to a, read a, move to b, read b and subtract a from b**). However, it does not eliminate the other five operations associated with AD (**retrieve weight, combine difference  $a - b$  and weight, retrieve overall total score, add weighted difference to total score and store total score**). With the COMPARE, the formula for AD shown in Table 1 becomes  $(c - 1) * (5 * r)$ . For this experiment a ten-alternative by eight-attribute problem was used, thus AD required 360 (i.e.,  $(10 - 1) * (5 * 8)$ ) EIPs. In this manner the COMPARE function brings the processing cost of AD closer to that of EBA and CNJ. Given that the additive strategies are recognized as more accurate, decision makers who place a high value on accuracy should adopt the AD strategy.

Based upon this reasoning and the results from E1 and E2, we would expect:

**H1. Subjects with high AD support will exhibit a search pattern that is more strongly oriented by attributes than those in the low AD support group.**

**H2. Subjects with high AD support will employ the additive difference strategy, those with low AD support will use elimination based strategies.**

**H3. Subjects with high AD support will use a greater number of dependent evaluations than those with low AD support.**

(ii) *EBA Support Hypotheses.* High EBA support reduces the processing effort of using EBA. The results of E1 and E2 indicated that the decision aid led to the use of EBA and that CONDITIONAL DROP influenced this. For low EBA, in absence of the CONDITIONAL DROP, the processing demands of EBA and CNJ are approximately equal, since in both cases the decision makers have to perform the move, read and compare operators. Also, for low EBA, without the CONDITIONAL DROP, the use of the DROP command is still helpful in reducing the tracking effort and in reducing memory errors. Under these conditions, EBA is slightly less effortful for memory and equally accurate for tracking, and is similar in terms of processing effort. Given the small difference in effort required, it is likely that both EBA and CNJ may be employed in these conditions.

Based upon the results from E1 and E2, we expect that:

**H4. Subjects with high EBA support will exhibit a search pattern that is more strongly oriented by attributes than those in the low EBA support group.**

**H5. Subjects in the high EBA condition will use EBA, while those in the low EBA condition will use either EBA or CNJ.**

#### (d) *Experimental Procedures*

The task environment was the same as in E1 and E2. A single ten-alternative by eight-attribute problem was employed with the same data set used in the previous studies.

The subjects were 28 first-year MBA students, of whom 11 were female. Participation was voluntary. All subjects were paid \$15 to complete the exercise. Procedures for running the experiment were identical to those employed in E1 and E2.

#### (e) *Presentation of Findings*

The main and interaction effects of AD and EBA support for the dependent variables “direction of search” and “dependent evaluations” were analyzed using a  $2 \times 2$

TABLE 7  
ANOVA Results-Direction of Search (Experiment 3)

SOURCE	DF	F-value	P-Value		ADDITIVE DIFFERENCE		
					High	Low	
AD Support	1	0.03	0.87	High Elimination by Aspects	71 (27) <sup>a</sup>	70 (39)	70.5
EBA Support	1	3.72	0.07				
AD*EBA	1	0.01	0.93	Low Elimination by Aspects	37 (67)	32 (56)	34
					54	50	

<sup>a</sup> Mean Score (Standard deviation): -100 = pure alternative search, +100 = pure attribute search.

between subjects factorial design (SAS 1985). Overall strategy was examined using Chi-square tests.<sup>7</sup>

Ten protocols, representing approximately 500 coded statements, were tested for inter-coder reliability using the same approach as in E1 and E2. The raw proportion of agreement was 0.82; the value for Kappa was 0.72.

(i) *Additive Difference Results.* The mean values for the treatments and the significance levels for the hypothesis tests are shown in Tables 7, 8 and 9.

Neither direction of information search nor strategy was influenced by the level of AD support. Consistent with E1 and E2, all subjects used elimination strategies.

Those with high AD support engaged in significantly more dependent evaluations ( $p = 0.02$ ). In the high AD group, 28% of the protocol statements involved dependent evaluations, whereas only 13% of protocol statements in the low AD group were dependent evaluations (see Table 9).

(ii) *EBA Results.* The results of the hypothesis tests are summarized in Tables 7, 8 and 9.

The level of support for EBA had a weak influence on the direction of information search ( $p = 0.07$ ). The high EBA group employed a strong attribute-based search (direction of search score = 70.5 for high EBA; 34 for low EBA).

The strategy assessment using a Chi-square analysis (Table 8) shows that those with high EBA support followed an EBA strategy exclusively; two-thirds of those with low EBA support used EBA, one-third used CNJ ( $p = 0.03$ ).

#### (f) Discussion of Experiment 3

In both E1 and E2 we noted a tendency to adopt strategies which minimize effort requirements given the commands available. A similar effect appears in E3. In lim-

<sup>7</sup> In all cases, because of the small cell sizes, Fisher's exact test was used in addition to the Chi-square. Conclusions derived from both tests were always consistent.

TABLE 8  
*Categorical Modeling Results-Strategy (Experiment 3)*

SOURCE	DF	CHI-SQUARE	P-value	
AD Support	1	0.32	NS	
EBA Support	1	7.95	0.005	
AD*EBA	1	0.32	NS	
High Elimination by Aspects		Low Elimination by Aspects		
	Low Additive Difference	High Additive Difference	Low Additive Difference	High Additive Difference
Conjunctive	0 <sup>a</sup>	0	2	3
Elimination by Aspects	5	5	5	4

<sup>a</sup> Number of subjects using the specified strategy.

ited ways, each group of subjects appears to adapt their processing to reflect the menu of tools available to them. This adaptability appears to be the result of changes in effort associated with using a subcomponent of a strategy. When a particular strategy, or substrategy, is made less effortful, it is more likely to be used (e.g., there were more dependent evaluations for the high AD group). Conversely, when a particular strategy is made more effortful, some subjects move away from that strategy (e.g. lack of CONDITIONAL DROP reduces the number of decision makers using EBA). It would appear that seemingly minor design changes in a decision aid have the potential to influence decision processes. This is consistent with the general conclusion in the choice literature that decision makers are highly sensitive to even minor changes in task environments (Einhorn and Hogarth 1981).

TABLE 9  
*ANOVA Results-Dependent Evaluations (Experiment 3)*

					ADDITIVE DIFFERENCE		
SOURCE	DF	F-value	P-value		High	Low	
AD Support	1	7.00	0.02	High Elimination by Aspects	24 (16) <sup>a</sup>	12 (12)	18
EBA Support	1	0.81	0.38				
AD*EBA	1	0.29	0.59	Low Elimination by Aspects	32 (27)	14 (09)	23
					28	13	

<sup>a</sup> Mean percentage of dependent evaluations in protocol statements (standard deviation).

(i) *Additive Difference Support* The influence of high AD support on dependent evaluations indicates that it is possible to move decision makers in the direction of engaging in additive type strategies if some effort inducement is provided to do so. The COMPARE function made the dependent evaluation easier. The failure to find overall strategy effects can be traced back to the fact that only five of fourteen high AD subjects used the COMPARE function. Even then, it was only used for comparing the last two or three alternatives. No subject consistently used COMPARE throughout the search process. Users of the COMPARE function averaged 22 dependent evaluations. Those in the high AD treatment who were exposed to the COMPARE in the tutorial, but did not use it in the experimental session, averaged 12 dependent evaluations; while those in the low AD treatment averaged only six.

If the decision maker put a high weight on accuracy then we would expect that person to use additive difference when the COMPARE was available.<sup>8</sup> One common explanation for the failure of decision makers to use additive strategies is that they are desirable but too effortful. COMPARE reduces the effort associated with AD by approximately 50% though not down to the levels of effort associated with EBA and CNJ. The fact that we did not see extensive use of AD would appear to indicate that decision makers placed more weight on effort considerations than on accuracy or alternatively that they did not perceive a difference in accuracy between the two strategies.

(ii) *EBA Support.* The level of EBA support had more overall impact on strategy than did the level of AD support. Those in the high EBA group followed an EBA strategy. The CONDITIONAL DROP command was used by seven of 14 subjects a total of 19 times. All subjects who used CONDITIONAL DROP followed an EBA strategy. Furthermore, no subject in the high EBA condition used a CNJ strategy. Six of the seven subjects who never used CONDITIONAL DROP after completing the tutorial used EBA, while one subject used an additive strategy.

In the low support condition, strategy was mixed between CNJ and EBA. Given the decision aid without the CONDITIONAL DROP there is only a small difference in the total number of EIPs required to execute the two strategies. Thus, though subjects used both EBA and CNJ there is still a tendency towards the less effortful strategy, EBA.

## 8. Concluding Comments

### (a) *Limitations of the Study*

Prior to discussing the implications of the three experiments it is important to note their limitations. The limitations of these studies can be divided between those attributable to the limits of the underlying theory and those attributable to the operationalization of the studies. In terms of theory it should be noted that the cost-benefit model limits itself to an examination of an individual decision maker operating in isolation from organizational and environmental influences. As noted previously there are other decision theories which challenge this restricted view (Benbasat and Todd 1991). However, though we would not assert that effort is the sole criterion which influences decision maker behavior when using a DSS, we do believe that these studies show it to be an **important** factor and that it is useful to consider the effect of effort.

<sup>8</sup> This argument assumes that the decision maker recognizes AD as a more accurate strategy than EBA.

Methodological limitations stem from the data collection approach and the task setting. All data reported were based on the use of concurrent verbal protocols. This method of data collection is not without criticism. Todd and Benbasat (1987) provide a detailed discussion of the pros and cons of the application of verbal protocol analysis to DSS research. For the studies reported in this paper we note that intercoder reliability, while comparable to other protocol studies, was not high. Further, the labor intensive nature of protocol analysis implies the need for relatively small samples which could lead to lower than desired statistical power. With the pooled data for E1 and E2 this was not a major concern. With 28 subjects per treatment it was possible to detect a large effect ( $f = 0.4$ , see Cohen 1969, Chapter 8) associated with decision aid use with a power level of 80% for alpha at 0.05. In fact, both the main effects and interaction effects for pooled E1 and E2 data were significant as hypothesized. For E3, power was lower due to the smaller sample size (68% for detecting a large effect for alpha = 0.10). However, the only expected differences which did not materialize in E3 were those associated with H1 and H2. In these two cases, an examination of the means did not indicate the existence of a practically significant effect, (i.e. we do not believe that the small sample size was the only cause of a lack of significance).

Another issue in this study is the incentive of decision makers to make "high quality" decisions. Correct outcomes are difficult to determine for preferential choice problems. This means that in an experimental setting it is difficult to tie incentives to performance (though see, for example, Gossler et al. 1986 for one approach). In settings where the decision maker must live with the consequences of the decision, it may be that decision quality becomes a primary concern. In this respect extension to field settings or other task settings where benefits could be directly measured is important. In addition, it appears that the influence of the aid increases with problem size; thus, it may be that investigating larger problems would reveal further processing advantages.

Finally, as is the case with any study, it is not possible to generalize the findings here to other decision aids or other tasks. Nevertheless, the study has shown the importance of focusing on effort in trying to predict the impact of a DSS and this has implications for both research and practice.

### *(b) Implications of the Study and Research Challenges*

The results confirm the general finding of adaptability due to effort considerations advanced in behavioral decision theory and extends it to explaining DSS usage behavior. It appears that subjects adapt strategies in such a way as to maintain a low overall expenditure of effort. This implies that system designers can have considerable control over how information is processed. This should be viewed as both an opportunity and a warning. It is a warning in the sense that seemingly benign design decisions may indeed have a significant influence on subsequent behavior by systems users. For example, a home searching software package used by a major Canadian real estate firm is designed to direct individuals to specific properties based on specified criteria. In essence, the system leads decision makers to use an elimination strategy. It is not clear that this is either desirable or intended. In these experiments, adding or deleting commands such as CONDITIONAL DROP and, indeed, simply exposing subjects to the use of such commands, influenced strategies.

Systems designers need to think carefully about how they may influence decision



makers' strategies to avoid dysfunctional effects. At the same time, an opportunity is present to design systems to have intended positive influences, such as moving decision makers towards more desirable strategies. To do this it is necessary to provide tools which alter the **relative effort balance** associated with desirable and undesirable strategies. To summarize, the clear message here is that by altering the effort required to use specific components of a strategy, the strategy adopted by a decision maker can be influenced. System developers regularly make design choices which influence effort and should become aware of the potential impact of those choices.

There are two important research directions suggested by this study. One is for the conduct of more DSS studies which look at more complex, comprehensive decision support tools, but do so from the effort perspective and focus on process variables. This will help to test the applicability of the approach suggested here to a wider set of domains. Task domains which lend themselves more easily to direct measurement of both effort and accuracy would be fruitful ones to investigate. One such area is risky choice, which offers an easily measured normative solution as well as a growing body of research which uses a cost-benefit model (Johnson and Payne 1985; Bettman et al. 1986; Johnson et al. 1988; and Payne et al. 1988).

A second direction for further research leads back to more basic issues, focusing on the impact of individual tools on processing, memory and tracking. Here it would be possible to determine the influence of particular system features, and study in more detail how they impact strategy selection. For example, a study which examined a decision aid containing only various combinations of DROP, CONDITIONAL DROP and COMPARE could be used to isolate the effects of those functions on strategy. In particular, such studies could allow us to separate the effects of the individual functions and their relative impact on individual cognitive operations. This would take us beyond the current studies to determine exactly how and why the individual functions impact decision making processes. The value of such micro level studies would be in developing a toolkit of techniques which could then be employed by researchers studying comprehensive systems. Such a toolkit would also be of value to system designers in building support tools that were based on known decision behaviors.

We believe there is a need for studies at both the macro, or system level, and at the micro, or decision aid feature, level. Micro level research will identify the type of features which are beneficial and are candidates for inclusion in DSSs. Macro level research will identify the degree to which these features can be integrated into more realistic DSSs. It is likely that not all decision makers will use the same features to implement a given strategy, and some features will not be used when others which are perceived to be more powerful or easier to use are present.

Another important research issue is the measurement of effort in making decisions and in using a DSS. Kanter (1987) has noted that cognitive effort is an elusive construct. Future research of this type might take measures of effort which include counts of EIPs, counts of operators, or units of information employed. It is important to be able to separate the effort of following a particular strategy from the effort associated with learning and interacting with the DSS in order to determine the **net benefit** of the system. Ignoring the cost of using the system was a problem that Keen (1979) noted in his work on the "marginal economics of effort". In effect, although we may demonstrate that a certain command replaces some cognitive operations, if that procedure is difficult to use, there will be no perceived benefit in using it and as a

result users will elect not to do so.<sup>9</sup> Focusing on these two effort components will be important in future work.

In conclusion, the cognitive effort perspective has been found to be helpful in understanding the influence of DSSs on decision processes. In general terms, as the subcomponents of choice strategies are made more or less effortful decision makers will adapt their strategies in such a way as to limit their overall expenditures of effort. This extends the adaptability notion prevalent in the behavioral decision making literature to include adaptation to the types of computer-based support tools provided. The application of the theory to larger problem sizes, different reward conditions and task domains must be studied to determine the extent to which these findings can be generalized.<sup>10,\*</sup>

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<sup>9</sup> For the studies reported here users made few errors and post-experiment debriefings indicated that subjects found the decision aids easy to use.

<sup>10</sup> The software used in these studies is available from the authors upon request.

\* Gerardine DeSanctis, Associate Editor. This paper was received on June 4, 1990 and has been with the authors 4 months for 1 revision.

#### Appendix 1: Characteristics of Preferential Choice Strategies

	AC	AD	EBA	CNJ
Information Used <sup>1</sup>	100%	100%	<100%	<100%
Variability of Attributes Examined Per Alternative <sup>2</sup>	Constant	Constant	Variable	Variable
Direction of Search (by)	Alternative	Attribute	Attribute	Alternative
Elimination Prior to Choice	No	Yes	Yes	Yes
Ratio of Dependent to Total Evaluations <sup>3</sup>	Low (<50%)	High (>50%)	Low	Low
Compensatory Statements <sup>4</sup>	Yes	Yes	No	No

Additive-Compensatory (AC): Each alternative is evaluated independently. For each attribute a weight is assigned. The weights and attribute preference values are combined and summed. The alternative with the highest score is selected. This strategy is compensatory; high values offset low values.

Additive Difference (AD): This strategy is similar to AC. The primary difference is that two alternatives are compared at a time and weighted differences between attributes are summed. From the pair, the better alternative is retained for further comparison.

Elimination by Aspects (EBA): Thresholds are set for each attribute. All alternatives are evaluated along a

<sup>1</sup> A subject was determined to have used a specific strategy if at least five of the six criteria were consistent with that strategy. This is consistent with the approach used by Biggs et al. (1985) and Jarvenpaa (1988).

<sup>2</sup> Variability is indicative of elimination of filtering strategies since some alternatives will be eliminated when only a partial set of information has been considered.

<sup>3</sup> Dependent evaluations involve comparison between two alternatives for a single attribute.

<sup>4</sup> Compensatory statements indicate that high values on one attribute offset low values on another for a given alternative.

common attribute. Alternatives which do not meet the threshold are eliminated. This procedure is repeated for each attribute until one alternative remains.

Conjunctive (CNJ): In this strategy each alternative is evaluated independently along its attributes. As soon as an attribute is found which violates a threshold the alternative is eliminated.

#### Appendix 2: Development of the Decision Aid

System development started from a theoretically defined set of functions. These functions were derived by decomposing the four choice strategies into their constituent elementary information processes (Bettman et al. 1986). These elementary processes help to identify the activities a subject would perform in pursuing any one of the choice strategies. Support functions relating to these processing activities were built into a system.

The system was then tested by providing test subjects access through an intermediary. These test subjects worked on two different problems: apartment selection and choosing an MBA program. Subjects described the function they wanted the system to perform and the intermediary entered the appropriate command. These test subjects had no a priori knowledge of the features built into the system. In this respect their design suggestions were not anchored by knowledge of the current system. When test subjects no longer requested functions not already built into the system, the system was considered to be complete. The final version of the decision aid contained a set of commands outlined in Table 3.

Thus, the functions built into the system have been theoretically derived from knowledge of preferential choice strategies and empirically validated through testing. It should be emphasized that these test subjects were not involved as experimental subjects in either E1 or E2, even though they were drawn from a similar population as the experimental subjects. The testing took place over a period of several months prior to conducting the studies reported here.

#### Appendix 3: Protocol Coding Categories (adapted from Jarvenpaa 1989)

1. *Independent evaluations* (IE) indicate processing by alternative because, in an independent evaluation, the subject evaluates the attributes of the alternative without any consideration to the attributes of the other alternatives.

2. *Dependent evaluations* (DE) indicate processing by attribute because, in a dependent evaluation, the subject evaluates the attributes of the alternative by comparing those attributes to the attributes of the other alternatives.

3. *Summations* (S) indicate compensatory processing because the calculations of sums make sense only if the subject believes that a low rating on one attribute *can be compensated* by a high rating on another attribute.

4. *Differences* (D) indicate compensatory processing because such arithmetic calculations make sense only if the subject believes that a low rating on one attribute *can be compensated* by a high rating on another attribute.

5. *Eliminations* (E) indicate noncompensatory processing because the use of elimination assumes that a deficiency on one attribute *cannot be compensated for by* the strength on another attribute. Once a deficiency has been identified, an alternative is immediately eliminated.

6. *Temporary Choices* (TC) indicate noncompensatory processing because subjects often do not explicitly state that the alternative has been eliminated, but state which alternatives are still being considered.

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