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Author(s): Raj Sethuraman, Catherine Cole and Dipak Jain

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Analyzing the Effect of Information Format and Task on Cutoff Search Strategies

Raj Sethuraman and Catherine Cole

*Department of Marketing
University of Iowa*

Dipak Jain

*Department of Marketing
Kellogg Graduate School of Management
Northwestern University*

An analytical framework is presented that specifies optimal search strategies when consumers use cutoff decision rules when information is formatted by brand or attribute and when the task is either screening alternatives or choosing the first acceptable alternative. The results show that formatting effects determine optimal processing strategies for screening but not for satisficing choice tasks. A laboratory experiment was conducted to test the validity of the analytical results. Most results were validated. However, under certain conditions, consumers use brand processing in choice tasks even when the analytical model predicts attribute processing. Results from a follow-up study suggest that this deviation occurs because brand processors have different subjective search costs than attribute processors.

Faced with a set of alternatives, each described on several attributes, decision makers may adopt several heuristics to simplify their choice task (see Bettman, Johnson, & Payne, 1991, for a review). One such heuristic, often cited in the literature, is the *cutoff* strategy. In this strategy, decision makers define a minimum acceptable level for each attribute and then choose the right brand(s) that exceed(s) the cutoff level on all attributes. Consumers appear to use such cutoff strategies in the initial phase of choice to form consideration sets

Requests for reprints should be sent to Raj Sethuraman, Department of Marketing, University of Iowa, 108 Pappajohn Business Administration Building, Iowa City, IA 52242–1000.

(Hauser & Wernerfelt, 1990; Huber & Klein, 1991; Lussier & Olshavsky, 1979; Payne, 1976). In this case, the consumers are using a cutoff strategy for screening or selecting the right brands for further processing.

Consumers may also use cutoff strategies to make final choices. For instance, pressed for time, a supermarket shopper may choose the first cereal package that is under \$3.00, has raisins, and has less than 2 g of fat per serving. This “choose the first right brand” strategy is commonly known as the *satisficing rule* and is well documented in the literature (Cole & Balasubramanian, 1993; Dickson & Sawyer, 1990; Grether & Wilde, 1984; Simon, 1955).

How do consumers implement the cutoff strategy? That is, how do consumers search for information to achieve their objectives of identifying the right brand(s)? Cereal buyers may first pick one brand and inspect the brand on the relevant attributes. If the first selected brand does not pass on any one of the attributes (say, it has too much fat), they may throw the brand out of the consideration set and then pick another brand. This process may continue until they achieve their purchase objective of screening or choice.¹ In this case, the purchasers are adopting a form of conjunctive strategy (Coombs, 1964). Or, more broadly, they are searching by brand; hence, we call this search method the *cutoff processing by brand* (CPB) strategy.

Alternatively, cereal buyers at the supermarket may look at the brands on display, select the ones with raisins, then select from this subset all the brands priced under \$3.00 (and so on) until they achieve their purchase objectives. These buyers are adopting a strategy that is close to what researchers describe as the *elimination by aspects* (EBA) strategy (Tversky, 1972). More broadly, we can say that these consumers are searching for information by attribute; hence, we call this strategy the *cutoff processing by attribute* (CPA) strategy.

A pertinent question one can raise in cutoff decision situations is as follows: When do consumers process by brand (CPB) or by attribute (CPA)? Early research, based on experimental evidence, suggests that variables such as stage of the decision process (Bettman & Park, 1980), the way the information is formatted (Bettman & Kakkar, 1977; Biehal & Chakravarti, 1982; Russo, 1977), and the number of attributes/alternatives (Payne, 1976) affect what strategies consumers use. In other words, consumers adapt their decision-making strategies to the context. Literature has extended some of these results and presented additional contextual factors that may affect decision behavior (Jarvenpaa, 1989; Kleinmuntz & Schkade, 1993; Payne, Bettman, & Johnson, 1992). For instance, Jarvenpaa (1989), extending an earlier result by Bettman and Kakkar (1977), found that how consumers process information is consistent with how graphic displays are organized, that is, by alternative or by attribute.

¹In this article, we use the terms *choice* and *satisficing choice* interchangeably, both mean “choose the first right brand” strategy.

The purpose of this article is to advance this rich and growing literature. By integrating analytical and experimental work, we obtained insights into how consumers use cutoff strategies. We built on the cost–benefit models in the literature (Grether & Wilde, 1984; Johnson & Payne, 1985; Ratchford, 1982; Shugan, 1980) by explicitly incorporating information format in an analytical model of cutoff strategies. General experimental findings (Bettman & Kakkar, 1977; Jarvenpaa, 1989; Russo, 1977) indicate that consumers process information the same way it is organized. We investigated whether information format also determines the optimal information-processing method in cutoff strategies. Our analytical results establish that information format always determines optimal information-processing methods when screening is the objective. But, when satisficing choice is the objective, we find that there are certain conditions when consumers should process information by brand, even though the information is formatted by attribute. In addition, we investigated what the optimal sequence of attribute inspection should be and found that consumers should process first those attributes that have low acquisition costs and low probabilities of passing the cutoff levels.

Then, we tested the results from the analytical model through a series of experiments. These experiments validate most of the results, emphasizing the usefulness of the cost–benefit framework. However, there are some deviations that provide additional insights into consumer processing strategies. Specifically, we observed consumers processing by brand when the model predicts attribute processing. We found that this deviation occurs because these consumers' perceived search costs differ from the actual costs.

Thus, we believe this article contributes to the literature in several methodological and substantive ways. From a methodological standpoint, first, we incorporated information format and the consumer's task into an analytical framework and investigated how these variables affect processing strategy. Previous research on information format has been primarily experimental, has not separately considered screening and choice, and has not explicitly studied the case of cutoff strategies. Second, we manipulated information format using processing time instead of through the traditional information display board. By manipulating the information format this way, we controlled the strength of the information format manipulation. Third, we recorded the requests for information on the computer, thus alleviating the need to ask consumers to verbalize their processing strategies as they screen brands or make a choice.

From a substantive viewpoint, the analytical model uncovered a general bias toward brand processing in the case of cutoff strategies when satisficing choice is the underlying objective. Our experimental work showed a bias toward brand processing even beyond what the analytical model predicted. We identified the factors that may potentially account for this bias and thus contributed to our general understanding of processing strategies.

We organized the article as follows. First, we provided the characteristics of

the analytical model and discussed the model results. Then, we tested whether consumers actually use the predicted processing strategy with experimental analysis. Finally, we provided our conclusions and directions for future research.

ANALYTICAL MODEL

Assumptions and Concepts

Consider a choice situation in which the consumer must evaluate m brands (alternatives) on n attributes with some given cutoff levels. The attributes may be discrete or continuous. Let,

p_i = Probability that a given brand will pass the cutoff level on the i^{th} attribute ($i = 1, 2 \dots n$).

f_i = Probability of failing on attribute i ($= 1 - p_i$).

c_i = Cost of processing (inspecting) the i^{th} attribute of a given brand. These costs can include the physical cost of acquiring and reading and cognitive-thinking costs, as conceptualized by Shugan (1980) and Johnson and Payne (1985).

b = Brand-switching cost—cost (difficulty) of switching from one brand to another on the same attribute. That is, b is the cost of moving to inspect another brand on an attribute after inspecting one brand on that attribute. It can include the physical cost (e.g., moving along the aisle to inspect the fat content of Post's cereal after inspecting the fat content of Kellogg's cereal) and the cognitive cost (e.g., shifting thoughts of brand from Kellogg to Post).

a = Attribute-switching cost—cost (or level of difficulty) of switching from one attribute to another for the same brand during information search, conceptualized the same way as the brand switching cost.

k = Attribute- and brand-switching cost—cost of switching from one attribute of one brand to another attribute of another brand.

As noted in Grether and Wilde (1984), we assumed the costs are fixed, known, and equal across brands, and that the p_i s are independent. In the cereal example, one can reasonably assume that raisin content, fat content, and price are independent. The "right" brand is that which passes the cutoff levels on all attributes. We assumed that there is at least one right brand in the expected sense.² In the event that a consumer does not find any right brand, we assumed

²The expected number of right brands is given: $ER = mp_1p_2 \dots p_n$. We assume $ER \geq 1$.

he or she does not buy any brand from the set. Finally, we assumed the consumer has no specific prior information about the brands except that any given brand will pass the cutoff level on attribute (i) with probability (p_i).

A decision maker will benefit from identifying the right brand(s) that pass(es) the chosen cutoff level on all attributes. Given the search objective (screening or satisficing choice) and the cutoff levels, the benefit obtained from the search process is fixed and equals the utility or satisfaction derived from selecting the right brand. Hence, the choice strategy that enables consumers to achieve their objective of finding the right brand(s) by expending the least cost (effort) is the one with the maximum net gain. Thus, consumers should prefer the strategy that achieves the objective at the least cost.

Description of Choice Strategies

In the CPB strategy, the consumer picks a brand and inspects the attributes one after another. If a brand does not pass the cutoff on any attribute, the consumer eliminates that brand and inspects the next brand. When screening is the objective, the consumer stops when all the right brands are identified; when choice is the objective, the consumer stops when the first right brand is identified. In the CPA strategy, the consumer inspects all brands on the first attribute. Then, the consumer inspects the second attribute of those brands that pass the cutoff level on the first attribute and so on. When screening is the objective, the consumer stops when he or she identifies all the right brands. When choice is the objective, the consumer stops once he or she identifies the first right brand.

Description of Format Conditions

In some situations, information may be neither organized by brand nor by attribute. For instance, information on attributes of different brands or objects may be arranged in a matrix form (e.g., comparative charts in *Consumer Reports*). In this case, the effort required to move from one information piece to any other information piece, whether the information is related to the same brand/attribute or different, is the same. That is, $k = a = b$. We call this the neutral format condition.

Often, however, information is arranged by brand. For most consumer packaged goods, the manufacturer prints information on brand attributes on the package. Similarly, in a car-buying situation, it is easier to drive to a dealer's showroom and inspect all the attributes of the car before driving to another dealer to inspect another car. That is, the cost of switching from one attribute to another of the same brand (a) is less than the brand-switching cost (b). Further, in general, when the consumer switches from one brand (or dealer) to another, the switching cost is the same whether the next attribute

inspected is the same as the one previously inspected (cost = b) or different (cost = k). For example, suppose a consumer has just inspected the price of Used Car A. The transition cost involved in seeking information about Car B in another dealership is the same (equal to the driving and asking time) whether the consumer asks about Car B's price or transmission or mileage. Thus, when information is organized by brand, $k = b > a$. We call this the brand format condition.

In some situations, information is arranged or is easily available by attribute. For instance, cereals in supermarkets may be arranged as those with high sugar, raisins, low fat, and so on. Flight information of airlines is arranged by travel time, destination, and so on. Some phone services (called *City Line* in some places) offer various types of information about different cities through different phone numbers. You call one number to get information about weather in different cities, another phone number to get sports information for the same set of cities, and another number to get road repair information. In all these cases, the cost of switching from one brand to another on the same attribute (b) is less than the attribute switching cost (a). Further, in general, when the consumer switches from one attribute to another, the switching cost is the same no matter whether the next brand inspected is the same as the one previously inspected (cost = a) or different (cost = k). Thus, when information is organized by attribute, $k = a > b$. We call this the attribute format condition.

ANALYTICAL RESULTS

Optimal Search Strategy

The expected costs incurred in using brand processing for screening (EC[CPBS]) and for choice (EC[CPBC]) and the expected costs incurred in using attribute processing for screening (EC[CPAS]) and for choice (EC[CPAC]) for a given attribute sequence, $1, 2 \dots n$, are provided in Table 1. The derivations of these expected costs are given in the appendix.

The following results identify the optimal (lower cost) strategies under the three information format conditions—neutral, brand, and attribute—for a given attribute-processing sequence, $1, 2 \dots n$. Proofs of the results are given in the appendix.³

Neutral format ($k = a = b$)

Result 1. When screening is the objective, the expected costs of processing by brand and attribute are identical.

³Due to space constraints, we provide the proofs only for Results 1 through 4. The proofs of Results 5 and 6 are available from the authors.

TABLE 1
Expected Costs

Processing Method	Objective	Notation	Expected Cost
Brand	Screening	$EC(CPBS)$	$m(EB) + ma(EP) + (m - 1)b + (m - 1)p_1(k - b)$
Brand	Choice	$EC(CPBC)$	$[EB + a(EP) + b + (k - b)p_1] \left[\frac{1 - F^m}{1 - F} \right] - [b + (k - b)p_1]$
Attribute	Screening	$EC(CPAS)$	$m(EB) + mb(1 + EP) - nb + (n - 1)k - (k - a) \sum_{i=1}^{n-1} p_i$
Attribute	Choice	$EC(CPAC)$	$m(EB') + mb(1 + EP') - (n - 1)b + (n - 1)k - (k - a) \sum_{i=1}^{n-1} p_i + (c_n + b) \left[\frac{1 - F^m}{1 - F} \right] - \prod_{i=1}^{n-1} p_i - b \left[\prod_{i=1}^{n-1} p_i \right]$

Note. $EB = c_1 + p_1c_2 + p_1p_2c_3 + \dots + p_1p_2 \dots p_{n-1}c_n$; $EB' = c_1 + p_1c_2 + p_1p_2c_3 + \dots + p_1p_2 \dots p_{n-2}c_{n-1}$; $EP = p_1 + p_1p_2 + p_1p_2p_3 + \dots + p_1p_2 \dots p_{n-1}$; $EP' = p_1 + p_1p_2 + p_1p_2p_3 + \dots + p_1p_2 \dots p_{n-2}$; $F = 1 - p_1p_2 \dots p_n$

Result 2. When satisficing choice is the objective, brand processing has a lower expected cost than attribute processing.

Brand format ($k = b > a$)

Result 3. When information is formatted by brand, despite whether the objective is screening or satisficing choice, brand processing has a lower expected cost than attribute processing.

Attribute format ($k = a > b$)

Result 4. When information is formatted by attribute and screening is the objective, attribute processing has a lower expected cost than brand processing.

Result 5. When information is formatted by attribute and satisficing choice is the objective, both brand processing and attribute processing can be lower cost strategies under certain conditions. Specifically, other things being equal, the results indicate the following:

1. An increase in attribute switching cost (a) increases the likelihood of attribute processing being the lower cost strategy (i.e., favors attribute processing).
2. An increase in brand switching cost (b) favors brand processing.
3. An increase in number of brands (m) favors brand processing.

4. An increase in number of attributes (n) favors attribute processing.

A summary of the optimal processing strategies under different conditions is given in Figure 1.

Attribute-Processing Sequence

In addition to identifying the lower cost strategies, we also investigated the optimal attribute-processing sequence.

Result 6. The expected cost of processing is the lowest when attributes are processed in the ascending order of c'_i/f_i where $c'_i = c_i + b$ for attribute processing and $c'_i = c_i + a$ for brand processing. That is, the attribute sequence $1, 2 \dots n$ will be optimal if and only if $c'_1/f_1 < c'_2/f_2 \dots < c'_n/f_n$

Discussion of Analytical Results

In this section, we provide some intuitive explanations for our results and compare our findings with those available in the literature.

Decision makers often use attribute cutoff levels for screening or identifying the acceptable alternatives for further processing (Payne, 1976). When screening is the objective, our results establish that the information-processing method matches the information format (Results 1, 3, and 4). This prediction is consistent with the general findings in the literature on information format (Bettman & Kakkar, 1977; Jarvenpaa, 1989; Russo, 1977). In addition, our analysis shows that the results hold for all values of the number of brands/attributes, processing costs, and probabilities of passing. In other words, when cutoff strategies are used for screening, information format (not the number of attributes or alternatives) is the primary determinant of the processing method. The reason is as follows: When screening is the goal, and attributes are processed in a given order, exactly the same items must be searched during either brand or attribute processing. Thus, only the switching costs created by the format will affect the cost of each method of processing.

When satisficing choice is the objective, brand processing is generally optimal in cutoff strategies. It is possible for brand processing to be optimal even when information is formatted by attribute. The reason is as follows: When choice is the objective (identify the first right brand), the CPA strategy can not identify the right brand until all $(n - 1)$ attributes of all the brands in the successively pruned set have been inspected. But, the CPB strategy can (with "non-zero" probability) identify the right brand after inspecting the last attribute of any brand and, hence, will stop once the first right brand is found.

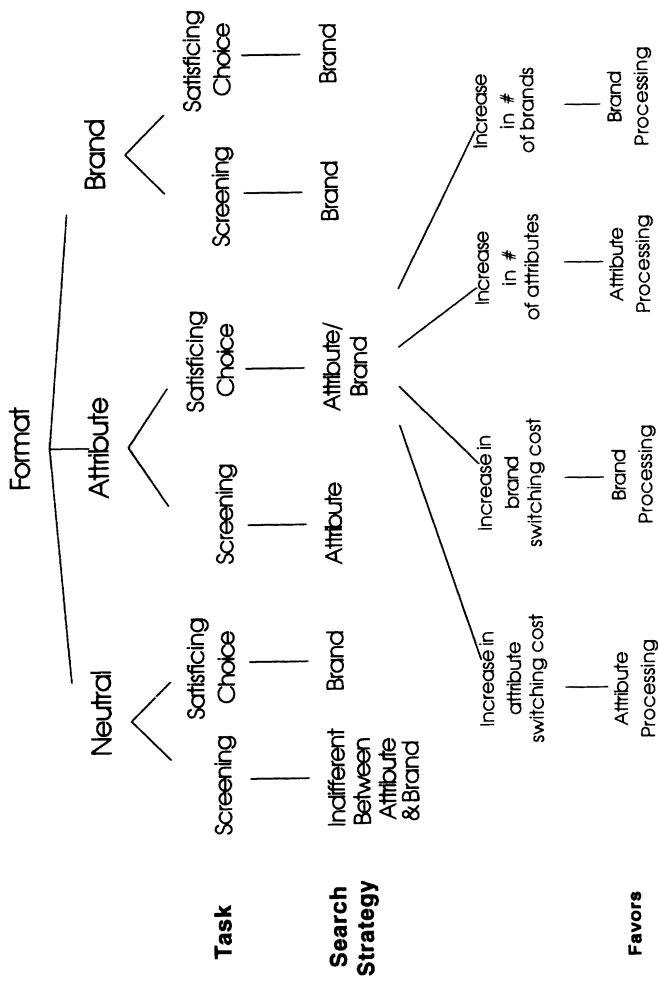


FIGURE 1 Summary of optimal search strategies.

Hence, the CPB strategy will have fewer total transitions and fewer brand transitions. However, it may have more attribute transitions than the CPA strategy. With neutral or brand formats, because the expected number of total transitions is lower for CPB than for CPA, and because CPB entails only more (equal or low-cost) attribute transitions, the expected costs of CPB are lower than that of CPA. That is, brand processing will be the optimal strategy despite the processing costs, probabilities, number of attributes, or the number of alternatives (Results 2 and 3).

However, when information is formatted by attribute ($k = a > b$), CPA or CPB can be optimal. Although brand processing has fewer total transitions, it entails relatively more (higher cost) attribute transitions and fewer (lower cost) brand transitions than attribute processing. Hence, for a given number of transitions, the larger the attribute transition cost (a), the greater the expected cost of brand processing because it has more attribute transitions. Hence, attribute processing is likely to be the low-cost strategy. Conversely, if the brand switching cost (b) becomes higher (close to the attribute switching cost), brand processing will be the optimal strategy because it has fewer brand transitions.

For given switching costs ($a > b$), when there are a large number of attributes (n), brand processors have to inspect several attributes per brand, incurring the relatively higher cost attribute transition each time. Hence, attribute processing is likely to be optimal. Conversely, when the number of brands (m) is large, attribute processing entails substantially large number of brand transitions for each attribute, thus making it more costly. Hence, brand processing will be optimal.

Qualitatively, Result 5 implies the following: Strong attribute formatting effects (large a and small b), smaller numbers of brands, or larger numbers of attributes tend to favor attribute processing. Weak attribute-formatting effects (a not very different from b), larger number of brands, and smaller numbers of attributes tend to favor brand processing.

Researchers (e.g., Payne, 1976) have suggested that decision makers use attribute processing to prune the set of alternatives when there are large numbers of brands. Our results indicate that this notion may not extend to the case of satisficing choice. In fact, with many brands, other things equal, processing by attribute will be costlier than processing by brand.

Result 6 states that the attribute that has a lower cost of processing and a higher chance of failing should be inspected first. Consumers can discard wrong brands most quickly by processing that attribute on which the brands are most likely to fail. If the probability of failing is equal across attributes, then consumers should first process attributes with the lowest processing costs. Grether and Wilde (1984) arrived at a similar result for a conjunctive satisficing utility model. We show that the result holds for a broader class of cutoff screening and choice strategies. Simonson, Huber, and Payne (1988) also

showed that consumers acquire information earlier if prior uncertainty is higher.

Next, we tested the results from the analytical model to see if they are consistent with observed consumer behavior in an experimental setting.

EXPERIMENT 1

We began with the premise that consumers search for information in the manner that minimizes effort (Beach & Mitchell, 1978; Simon, 1955). We further assumed that the information available to the consumers about different brand alternatives is formatted in one of three ways: by neutral, brand, or attribute. Then we asked whether the strategies that a consumer actually uses under each formatting condition will vary according to the search objective (screening or choice) and/or the number of brand alternatives and the number of attributes. We also tested whether consumers adopt the optimal sequence of attribute inspection as predicted by Result 6. Specifically, we tested the following hypotheses (Hs):

- H1: In the neutral format condition, consumers are indifferent between attribute and brand processing in the screening task, but they process by brand in a choice task, despite the number of brands/attributes, as predicted by Results 1 and 2.
- H2: In the brand format condition, consumers process by brand in both screening and choice tasks, despite the number of brands/attributes, as predicted by Result 3.
- H3: In the attribute format condition, consumers process by attribute in the screening task, and they use the lowest cost processing strategy in a choice task, as predicted by Results 4 and 5.
- H4: Other things equal, consumers process the attributes in ascending order of probability of passing (p_i) and cost of processing (c_i) in screening and choice tasks, as predicted by Result 6.

Method

Experimental design. We designed 12 separate interactive search programs using SEARCH MONITOR (Brucks, 1988) to study how three variables—Information Format, Consumer Task, and the Number of Brands/Attributes (referred to hereafter as Format, Task, and Brand/Attributes, respectively)—affect search behavior.⁴ The specifics of each search pro-

⁴SEARCH MONITOR is a micro computer program available from Merrie Brucks (Marketing Department, University of Arizona, Tucson). It allows researchers to design information

gram varied according to a $3 \times 2 \times 2$ design (Format—Neutral, Brand, or Attribute \times Task—Screening or Choice \times Number of Brands/Attributes—six Brands and six Attributes or nine Brands and four Attributes). Format and Brands/Attributes were between-subject factors, and Task was a within-subject factor. About half the subjects completed the screening task first; the other half completed the choice task first.

Procedure. Subjects were 220 undergraduate business students. They completed the study in groups of 10 to 12 at individual terminals in a computer laboratory. Individual terminals were separated by partitions. The initial computer screens that each subject saw provided instructions on how to use the computer keyboard. Then, the subjects completed two practice tasks and two experimental tasks. The practice tasks familiarized subjects with how to use the computer, how to apply a cutoff rule, and how to conduct search and screening tasks. It took subjects about 45 min to complete the computer task; then, they filled out a written questionnaire and were debriefed.

During the experimental tasks, subjects were told that they were to imagine that a friend wanted to identify all (or choose the first) used car(s) that met certain criteria out of a pool of available used cars. They were encouraged to be as efficient and accurate as possible without guessing and were informed that guessers could be identified by inspecting the search protocols generated by the computer for each subject. To promote efficient processing, we indicated that we would rank and pay all subjects according to their efficiency (defined as completing the task correctly in the least amount of time) such that the most efficient (i.e., the top one third) would receive \$3.00, the average group would receive \$2.00, and the least efficient group would receive \$1.00.⁵

Independent variables. The independent variables are information format, task, and number of brands/attributes. These variables were operationalized in the following manner: Information format, a between-subject variable, had three levels. In the neutral format condition, the computer program simply indicated that information was available for each brand on each attribute. (The information appeared instantly.) In the brand format condition, the computer program indicated that the used cars were in different locations spread across town. To get information about a car different from the one just inspected, there would be a 20-sec delay to imitate the costs of driving across town to reach the other location. However, once the subject asked a question

search experiments in which subjects are successively presented with menu-type screens that are displayed on video terminals. The program can be adapted to manipulate the time delays. The modified program used in the experiment is available from the authors.

⁵However, all subjects were paid the same amount (\$2) after the experiments were completed to avoid discrimination on the basis of skills.

about a car, there would be only a 4-sec delay to get more information about the same car. Consumers were given practice instruction screens to experience a 20- and a 4-sec delay. In the attribute format condition, the computer program informed subjects that information was available from separate phone services about each attribute (similar to the City Line services explained earlier). The subjects learned that sellers with used cars registered their cars with each service. If, for example, the subject wanted mileage information about a car, he or she had to call the mileage phone line. It took 20 sec to imitate the time it would take to dial the phone and reach the service. However, once the subject got on a phone line, he or she could ask about any other cars with a minimal 4-sec delay while the service looked up the information.⁶ These subjects, too, were given practice screens to experience 20-sec and 4-sec delays.

Each subject completed both a screening and a choice task; thus, the task was a within-subject variable with two levels. In the screening task, consumers had to identify all the cars that met the cutoff rule. In the choice task, consumers selected the first brand that met the cutoffs. The order of these two tasks was randomized.

The number of brands/attributes, a between-subject variable, consisted of either nine brands and four attributes or six brands and six attributes. When there were nine brands of cars and four attributes provided about each car, subjects learned that they should either choose one or identify all (depending on the task) cars that met a cutoff rule on four attributes (e.g., the car should be made in Japan). When there was information about six brands and six attributes, subjects received the same attribute cutoff rule with two additional attributes.⁷ By using these two conditions we held the total amount of information available constant in both conditions.

Dependent variables. The computer program facilitates direct monitoring and coding of the order in which consumers acquire information by generating a file of information requests for each subject. From these protocols, we examined each information transition from the r^{th} inspection to the $r + 1^{\text{th}}$ inspection. On the $r + 1^{\text{th}}$ inspection, a consumer would have been forced to switch to another brand if, on the r^{th} inspection, the brand did not pass the cutoff on the attribute or all attributes of that brand had been inspected. In addition, a consumer would have been forced to switch to another attribute if, on the r^{th} inspection, all brands had been inspected on that attribute. Because these transitions were forced switches, they did not provide information about the consumer's propensity to process by brand or attribute. About 30% of the

⁶The time delays of 20 sec and 4 sec in the attribute and brand format conditions were determined to ensure that subjects in general could (a) perceive a difference between the two time delays and (b) complete the full experiment in about 1 hr.

⁷The attributes were chosen using a pilot survey of students.

total number of transitions were forced switches, and these were eliminated. Of the nonforced switches, if on the $r + 1^{\text{th}}$ inspection, the consumer acquired information on the same brand as the one on the r^{th} inspection, but of a different attribute, that transition constituted a case of intrabrand search. But, if on the $r + 1^{\text{th}}$ inspection, the consumer acquired information on the same attribute but of a different brand, that transition constituted a case of intraattribute search. If the $r + 1^{\text{th}}$ piece of information searched was neither within the same alternative nor within the same attribute as the r^{th} piece of information, that switch was considered a random shift and was excluded from the analysis. Less than 5% of the total transitions were of a random nature.

Following Payne (1976), a processing method score (X) was computed for each subject for each task using the formula,

$$X = \frac{\text{intrabrand transitions} - \text{intraattribute transitions}}{\text{intrabrand transitions} + \text{intraattribute transitions}}$$

The values of X range from -1.0 to $+1.0$. If X is greater than 0, it indicates brand processing; if X is less than 0, it indicates attribute processing; if X equals 0, it indicates the subject is neither a brand nor an attribute processor.

Results of Experiment 1

Initial analysis. First, we tested if the order in which subjects completed the screening and choice tasks affected their processing method scores. There was no significant order effect; therefore, we pooled the data from subjects who completed the screening and choice tasks in different orders. Second, the final questionnaire showed that subjects in the attribute-formatting conditions estimated that it took much longer to switch attributes (M estimated time = 15 sec) than subjects in the brand-formatting condition (M estimated time = 7 sec), $t(136) = 7.01, p < .01$. Similarly, subjects in the attribute-formatting conditions estimated that it took much less time to switch brands (M estimated time = 10 sec) than subjects in the brand-formatting condition (M estimated time = 20 sec), $t(136) = 9.8, p < .01$. Thus, subjects in both conditions noticed and understood our formatting manipulation. Finally, we tested for motivation differences across the three formatting conditions by asking subjects to indicate how accurate and efficient they tried to be on two 5-point Likert items. (The items were, "I tried to be as efficient as possible while searching," and "I tried to be as accurate as possible in my judgments about the cars.") We found no significant differences across the three groups, $F(2, 114) = 1.5, p < .23$.

Overall analysis. The overall main and interaction effects of format, task, and number of brands/attributes were tested through an analysis of variance

TABLE 2
Mean Processing Scores

Format Condition	No. of Brands/Attributes	Screening Task		Choice Task		n
		Optimal Processing Method	Mean Processing Score	Optimal Processing Method	Mean Processing Score	
Neutral	6/6	Indifferent	-.06	Brand	.53*	33
	9/4	Indifferent	.09	Brand	.44*	23
Brand	6/6	Brand	.91*	Brand	.93*	41
	9/4	Brand	.89*	Brand	.98*	20
Attribute	6/6	Attribute	-.07	Attribute	.27	38
	9/4	Attribute	-.48*	Attribute	.11	44

*Significantly different from 0, $p < .05$.

TABLE 3
Summary Table for ANOVA on Processing Score

Source	df	Sum of Squares	M Square	F Ratio
Between subjects				
Format	2	61.71	30.85	41.13*
Number of alternatives	1	.57	.57	.76
Format × Number of Alternatives	2	2.21	1.10	1.48
Error between	193	144.78	.75	
Within subjects				
Task	1	9.83	9.83	34.95*
Task × Format	2	3.18	1.59	5.66*
Task × Number of Alternatives	1	.03	.03	.11
Task × Format × Number of Alternatives	2	.93	.46	1.66
Error within	193	54	.28	

* $p < .01$.

(ANOVA). The cell means are reported in Table 2; the ANOVA results are in Table 3.

Several effects from the ANOVA results are pertinent. First, note that, consistent with expectations, the main effects of task and format are significant, but the main effect of the number of brands/attributes is not. In addition, the Task × Format interaction is also significant, $F(2, 193) = 5.66, p < .05$, and is represented in Figure 2. This interaction occurs because, in the neutral format and the attribute format condition, consumers engage in more brand processing when the task is choice than when the task is screening. Specifically, in the neutral format condition, using the appropriate t test (Winer, Brown, & Michels, 1991, p. 550), the processing mean for choice (.49) is found to be

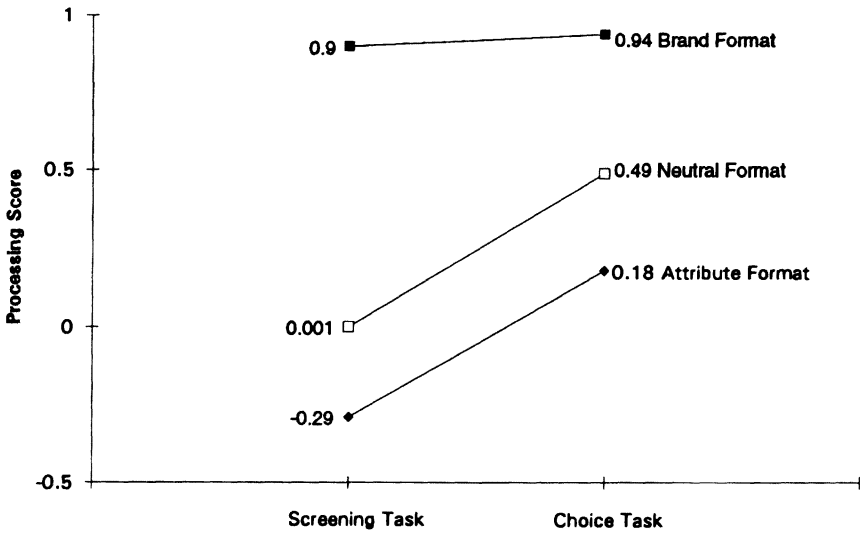


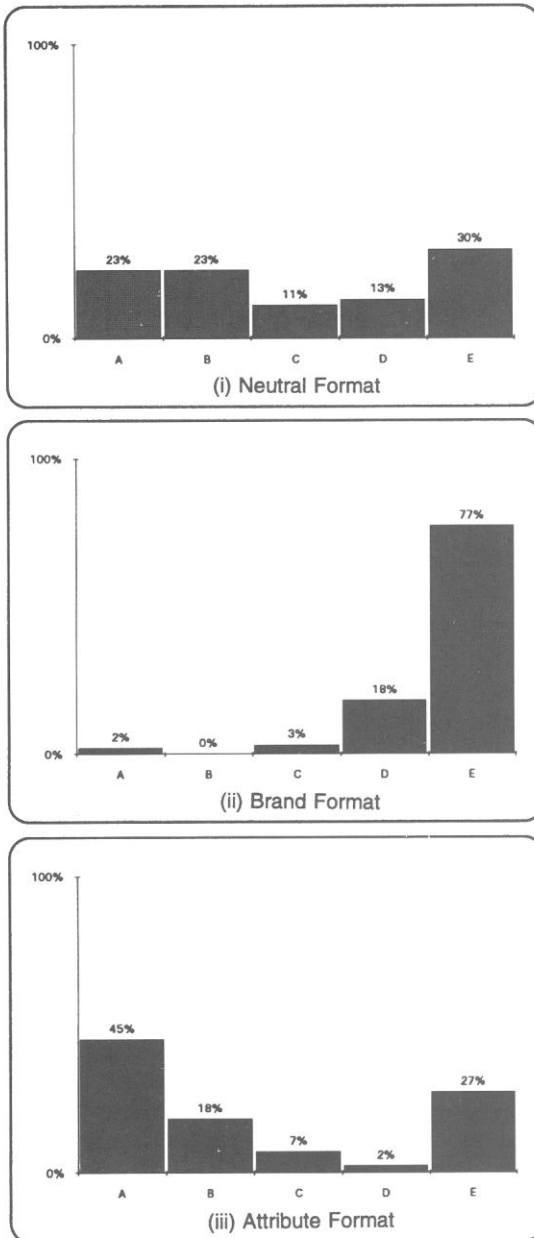
FIGURE 2 Task × Format interaction on processing score.

significantly greater than the processing mean for screening (.01), $t(55) = 6.72$, $p < .01$. In the attribute format condition, the processing mean for choice (.18) is significantly greater than the processing mean for screening (-.29), $t(80) = 7.94$, $p < .01$. However, in the brand format condition, consumers engage in the same amount of brand processing despite the task.

The distribution of processing scores (X) for each experimental condition, pooled across the two cases, is represented in Figures 3 and 4. A large number of people (over 70% of the sample) are either pure brand processors ($X = 1$) or pure attribute processors ($X = -1$). Of the remaining 30%, about 20% are dominant brand processors ($X \geq .5$) or dominant attribute processors ($X \leq -.5$). Very few (less than 10%) do both attribute and brand processing more or less equally in the same task ($-.5 < X < .5$). These findings suggest that (a) consumers decide on their strategy up front and continue with the same strategy until completion, and (b) our classification of brand/attribute processors may not be sensitive to the use of $X = 0$ as the cutoff.

Tests of hypotheses (H1–H3). We tested our hypotheses through a series of t tests. Specifically, we made inferences about the processing methods within a cell by testing whether the mean processing scores are greater than 0 (indicating brand processing), less than 0 (indicating attribute processing), or not significantly different from 0 (indicating neither brand nor attribute processing).

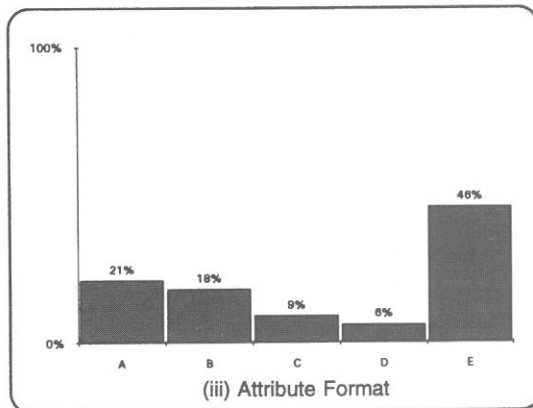
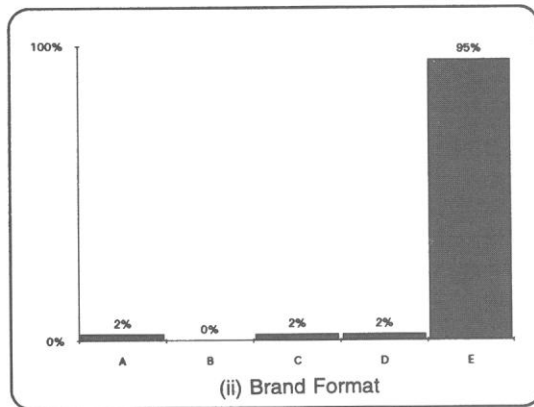
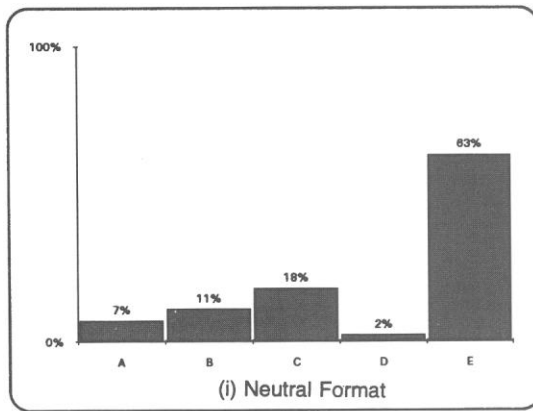
H1 states that, in the neutral format condition, there will be a task effect such that in the screening condition, subjects, on aggregate, should show no preference for brand or attribute processing; but, in the choice condition,



Note:

A	$X = -1$	Pure Attribute Processors
B	$-1 < X \leq -0.5$	Dominant Attribute Processors
C	$-0.5 < X \leq 0.5$	Attribute and Brand Processors
D	$0.5 < X \leq 1$	Dominant Brand Processors
E	$X = 1$	Pure Brand Processors

FIGURE 3 Distribution of processing scores—screening.



Note:

A	$X = -1$	Pure Attribute Processors
B	$-1 < X \leq -0.5$	Dominant Attribute Processors
C	$-0.5 < X \leq 0.5$	Attribute and Brand Processors
D	$0.5 < X \leq 1$	Dominant Brand Processors
E	$X = 1$	Pure Brand Processors

FIGURE 4 Distribution of processing scores—choice.

subjects will utilize brand processing. Consistent with this prediction, in the neutral format condition, the mean processing score for screening (.01), does not differ from 0, whereas the mean score for choice (.49) is significantly greater than 0, $t(54) = 5.03, p < .01$. The distributions of processing scores (Figures 3 and 4) also reveal that the number of brand processors (50%) and attribute processors (48%) are about the same in the screening task. In the choice task, 70% of the sample are brand processors ($X > 0$).

As per H2, in the brand format condition, the processing score is positive, indicating brand processing, regardless of whether the task is screening or choice. Again the results support this prediction. The average processing score for screening (.91) and for choice (.93) are significantly greater than 0, $t(60) = 22.8$ (screening), $t(60) = 25.7$ (choice), both $ps < .01$. The distribution of scores also reveals the strong format effect. Almost all the subjects (97%) processed by brand ($X > 0$).

H3 indicates that, when information is formatted by attribute and screening is the objective, attribute processing should be favored over brand processing. We find support for this prediction. The average processing score ($-.29$) is significantly less than 0, $t(81) = -3.01, p < .01$. However, the effect is not as strong as in the brand format condition. Some 67% of the subjects are attribute processors.

For the choice task, H3 does not provide clear predictions. Actual cost calculations with the numbers used in the experimental design indicate that, regardless of the number of brands/attributes, the expected costs with a CPA strategy is lower than that for CPB. That is, attribute processing should be favored. The processing mean for the choice condition (.18) is positive, indicating brand processing, though not significantly different from 0. Figure 4 reveals that 56% of the sample are brand processors.

Analysis of attribute-processing sequence (H4). We tested the implications of the analytical results related to optimal attribute inspection sequence (H4) by including information on attribute processing cost (c_i) and probability of passing (p_i) within the experimental design.

In the experimental conditions with neutral format (transition costs were not manipulated), we incorporated the cost of acquiring and processing information on a given attribute (c_i) through time delays ranging from 3 to 20 sec. For example, subjects were told that they would have to wait 18 sec to obtain information about the mechanic's rating of a car but only 9 sec to find out whether the car had an automatic transmission. Subjects were informed that the chance that a car would pass the cutoff level (p_i) was the same across all attributes. Our analytic results predict that, for any brand, consumers would process the attributes in the ascending order of processing cost (i.e., the attribute with the least time delay would be processed first and so on) regardless of the number of brands/attributes and the task. Because the coding and testing procedure involved in testing the order sequence is intensive and time-consum-

ing, and because we did not expect the results to be different across groups, we chose the condition with the larger number of attributes, the neutral format—six brand, six attribute—condition, for our analysis.

In the other four experimental conditions in which information format costs were manipulated, we set the processing costs to 0 and varied the probabilities of passing (p_i). The subjects were given the probabilities of passing for each attribute and were told that these probabilities were based on estimates available from the local market. For example, they were told that from previous experience they knew that about 55% of all used cars were made in Japan. The chance of passing on a given attribute in the experimental set more or less corresponded to the stated probabilities. Again, our results predict that consumers would process in the ascending order of the probability of passing in all experimental conditions. We chose two representative experimental conditions for our analysis: the attribute formatted 6 brand/6 attribute condition and the brand formatted 9 brand/4 attribute condition.

To test H4, we adopted a modification of the nonparametric test procedure described by Page (1963) for ordered alternatives:⁸ $H_0: \theta_1 = \theta_2 = \dots = \theta_n$ and $H_a: \theta_1 \leq \theta_2 \leq \dots \leq \theta_n$, where at least one inequality is strict. θ_i in this case is the sum of ranks across brands for a given attribute (i). The details of the statistical test are described in the appendix. The procedure computes the standard normal (z) statistic.

In the neutral format condition, where we tested whether consumers processed attributes in the ascending order of the cost of acquiring attribute information, the z statistics are 6.98 for screening and 8.08 for choice. In the attribute format condition, where we tested whether consumers processed attributes in the ascending order of the probability of passing the cutoff, the z statistics are 6.07 for screening and 8.21 for choice. Significant z scores (> 2) are also obtained in the brand format condition. Thus, subjects appear to inspect attributes in the predicted order.

Summary of Experiment 1

Our analytical results regarding optimal processing methods when the task changes from screening to choice match observed processing behavior in the neutral format conditions. In screening situations, consumers as a group were more or less indifferent between brand and attribute processing; but, in choice situations, consumers clearly favored brand processing. Our analytical and experimental results also converged in the brand format conditions. Here subjects, regardless of the number of brands/attributes and the task, favored

⁸Simple rank correlation is not appropriate for testing processing sequence because the data are only partially rank ordered (some brands were not inspected at all or were inspected on only a few attributes).

brand processing. However, in the attribute format condition, we found some deviations from predictions. In particular, consumers tended to favor brand processing for choice tasks when attribute processing was theoretically the more efficient strategy. The findings also indicate that consumers process attributes in the ascending order of processing costs and probability of passing. Apparently, consumers use prior information about product attributes to devise optimal attribute-processing sequences.

Overall, the decision makers appear to adapt to contextual factors, as predicted by the analytical model, except in one case of attribute formatted choice task. We conducted a follow-up experiment to identify why decision makers may use brand processing when performing choice tasks in the attribute format condition, even though our analytical model predicts attribute processing.

EXPERIMENT 2

We speculated that the difference between observed and predicted results may be due to the difference between the perceived subjective costs/probabilities, which consumers use in selecting a search strategy, and the objective costs/probabilities, which we use to make predictions.

For example, subjective transition costs (time delays) can differ from objective transition costs (Hornik, 1984; Kellaris & Kent, 1992). This difference in transition cost translates into a difference between objective and subjective strength of the format effects. The objective strength of the format effect is the difference between objective attribute transition cost (waiting time) and brand transition cost which equals $(20 - 4) 16$ sec. The subjective strength of the format effect is the difference between perceived attribute and brand transition costs (waiting times). A closer look at the data from Experiment 1 reveals that the objective and subjective strength of the format effects do differ, especially in the attribute format condition. In this condition, the subjective strength of the format effect (5 sec) was in the right direction, but it was different from the objective strength of the format effect (16 sec). In terms of our model, $a_{\text{subjective}} - b_{\text{subjective}} \neq a_{\text{objective}} - b_{\text{objective}}$.

The possibility of consumers perceiving the waiting times to be different from the objective waiting times can potentially explain why some people process by brand even though our prediction, based on objective costs, indicates attribute processing.⁹ Result 5 suggests that, in the attribute formatted choice condition, as the strength of the format effect gets weaker, people will be more likely to brand process. Hence, if subjective transition cost is a

⁹We thank Eric Johnson for suggesting this potential explanation.

plausible explanation, then brand processors should perceive weaker formatting effects (i.e., smaller differences in waiting times) compared to attribute processors.

Some consumers may perceive additional costs not captured by waiting time. For example, they may see that attribute processing requires more effort (takes more thinking resources) than brand processing. In attribute processing, there is a need to keep track of which brands passed on all previous attribute inspections. This effort can lead to additional costs. If some subjects feel that this cost is high, relative to others, then they are likely to be brand processors.

Consumers may also differ in their perceptions of the probability of a selected alternative passing on all the attributes. In particular, subjects who find a brand that passes on one attribute may overestimate the probability that the brand will pass on remaining attributes and, hence, process by brand. (In other words, brand processors may overestimate p_i .) This argument is similar to that given by Klein and Yadav (1989) when they suggested that decision makers may overestimate their accuracy.

The purpose of the follow-up study is to assess if differences between perceptions and objective values are plausible explanations for the deviations from predicted results. In particular, we investigated whether, compared to attribute processors, brand processors:

1. Perceive the difference in time between waiting for information for another brand and another attribute to be lower.
2. Feel there is greater effort involved in keeping track of information during search.
3. Tend to assign greater probability of passing on remaining attributes given that a brand has passed on some attributes.

Design of Experiment 2

In this experiment, subjects completed the choice task in the 6 brand/6 attribute formatted condition. We selected this cell because in the previous experiment the mean processing score was positive and 61% of the subjects in this condition favored brand processing although attribute processing was more efficient. Once the choice task was completed, subjects filled out a questionnaire eliciting perceived cost and probability information. Subjects were then debriefed and excused.

Operationalizations of variables. We developed two measures of perceived transition costs. In one measure, we collected attitudinal data relating to perceived waiting time with a four-item Likert scale (coefficient alpha = .8).

(Two example items are as follows: “In the used car experiment, I had to wait a lot longer for some information than for other information,” and “In the used car experiment, I didn’t really notice many differences in how long I had to wait for information to appear on the screen.”) Subjects indicated how much they agreed or disagreed with the four statements on 5-point scales. We recoded items so that a higher number indicates that the consumers perceived greater differences in time between waiting for attribute information and waiting for brand information. Another measure came from two questions asking consumers to imagine that they were explaining to a friend how to search for information in this task. They had to indicate how many seconds their friend would have to wait if he or she had just asked about the mechanic’s opinion of a car and if he or she wanted to know the country of origin for the same car (attribute transition). Then, they also had to indicate how long their friend would have to wait if he or she had just asked about the mechanic’s opinion of a car and now wants to know the mechanic’s opinion of a different car (brand transition). The difference between the first time and the second time yielded one measure of perceived costs that we call *subjective time differences*.

We also measured cognitive effort in two ways. First, consumers completed a two-statement, 5-point perceived cognitive effort scale. The two items correlated .66 (sample item: “In the used car experiment, it took a lot of effort to keep track of all the information”). Second, consumers completed a perceived use of luck scale with two statements that correlated .63 (example item: “Thinking back to how I found an acceptable used car, I would say that I relied mostly on luck”). This scale was coded so that the higher the number, the more the subject had relied on luck.

We obtained perceived probabilities by giving subjects two hypothetical scenarios. In Scenario 1, subjects were told, “Suppose you have just found out that a different car (call it *ZA*) passed on one attribute (say mechanic’s opinion), what is the probability that it will pass on all the remaining attributes?” They had to check 1 point on a 7-point scale ranging from 0% to 100%. In Scenario 2, subjects learned that a different hypothetical brand had passed on two attributes and that they had to estimate the probability that it passed on the remaining attributes.

Results of Experiment 2

Because we were interested in differences between brand and attribute processors, we divided our sample into attribute and brand processors using the Payne (1976) measure described earlier. Of the 58 subjects, attribute processors ($X < 0$) were 27% of the sample and brand processors ($X > 0$) were 63% of the sample. Table 4 contains means and *t*-test results for differences between attribute and brand processors on each of our dependent variables.

TABLE 4
Results of Experiment 2

<i>Variable</i>	<i>No. of Items</i>	<i>Attribute Processors^a</i>	<i>Brand Processors^b</i>	<i>T Value</i>
Perceived transition costs				
Perceived waiting time	4	13.93	11.97	1.9*
Subjective time difference		11.38	2.0	2.4**
Cognitive effort				
Perceived cognitive effort	2	4.63	4.27	.57
Perceived use of luck	2	3.87	4.45	-1.06
Perceived probabilities				
Probability 1	1	3.43	3.9	-1.31
Probability 2	1	4.33	4.45	-.196

^a $n = 16$. ^b $n = 37$.

* $p < .06$.

** $p < .01$.

There were significant differences between brand and attribute processors on our two measures of perceived transition costs. Brand processors perceived lower waiting times and estimated smaller time differences between attribute and brand transitions than attribute processors. None of the other differences were significant.

Summary of Experiment 2

Payne (1982) suggested that processing strategies are contingent on the environment, the decision makers' perceptual process, as well as on their priorities and motivation. In Experiment 2, we investigated whether some decision makers did not adapt to the objective environment (attribute format) as predicted by the model because of individual differences in perceptions. Specifically, we found that brand processors perceived the (subjective) difference in waiting time to be less than that of attribute processors, and this may be a reason why they processed by brand.

Why did differences between subjective and objective waiting times lead to deviations from predicted experimental outcomes only in the attribute formatted choice condition? The analytical model provides an answer. The analytical results state that, in all conditions other than the attribute formatted choice task, our predictions depend only on the direction of the format effect, not on the strength of the format effect. Hence, as long as consumers perceive one type of transition cost to be greater than the other as manipulated, they should adopt the predicted strategy. The strength of the format can lead to deviations only in the attribute formatted choice condition.

CONCLUSION

In this article, we attempted to understand consumers' implementation of cutoff strategies under different contexts through an integration of analytical and experimental approaches. We developed a cost minimization model of a cutoff strategy that incorporates information format, task, the number of brands and attributes, processing costs, and probabilities of brands passing the cutoff level on a specific attribute. We compared the costs of attribute- and brand-processing strategies.

The main results of the study are (a) when screening (selecting the right brands for further consideration) is the task, consumers process information the same way it is organized (by brand or by attribute) despite the number of brands/attributes, probability of passing the cutoff, and so on; (b) when satisficing choice (choose the first right brand) is the task, consumers predominantly process by brand even when information is formatted by attribute; (c) consumers process first those attributes that have low inspection costs or low probabilities of passing the cutoff levels; and (d) consumers' perceived search costs (waiting times) can differ from the actual search costs.

These results have some interesting managerial implications. The result that consumers predominantly process by brand when using satisficing choice strategies has implications for presentation of product information. It implies that, when satisficing choice is used (e.g., in the supermarkets), brand managers should ensure that their brand is processed first (e.g., by inducing the retailers to place the brand in end-aisle displays so that they are inspected before the brands on the shelf). The result that consumers first process those attributes that are most discriminating has implications for product positioning and advertising. It is generally believed that a firm should promote one or two benefits on which the brand has a distinct advantage over other brands (Kotler, 1994, p. 307). In addition, our result suggests the need for stressing that the brand is one of the few with the desired attribute (e.g., Chrysler's earlier commercials stating that its cars are the only ones with air bags). By adopting this strategy, the firm can eliminate most of its competitors in the early stages of decision making.

Although the model pertains to cutoff decision rules in a specific context, some results can be extended to understand general decision making in other information presentation contexts. For instance, Stone and Schkade (1994) found that, within a matrix format (similar to our neutral format), if attribute information was on a common standardized scale, consumers processed by brand—as predicted in our cutoff choice framework. If information was presented on a unique scale, however, consumers processed by attribute. Our analytical results and experimental finding that subjective costs differ from physical or objective costs can provide one explanation for this result. In both the cases the objective transition costs are equal ($a_{\text{objective}} = b_{\text{objective}}$) but the

subjective transition costs can be unequal. In particular, in the case of a unique attribute scale, shifting from thinking about one unique attribute to another of the same brand ($a_{\text{subjective}}$) can be greater than shifting to the same attribute information of another brand ($b_{\text{subjective}}$). This difference may be a reason why attribute processing is observed. Future research is needed to explore the task and individual characteristics that affect perceived waiting times (transition costs).

There are several limitations that arise from the assumptions imposed on the model to improve parsimony and analytical tractability. We started with the premise that consumers will adopt cutoff strategies with predetermined cutoff levels. Hence, all our predictions pertain only to cutoff decisions. We have not included consumer updating or learning and have not considered the case of correlated attributes. Future research can relax the assumptions in the analytical model within the cutoff decision framework. For instance, correlation among attributes can be captured through a conditional probability of passing on one attribute given that it has passed on another. Moreover, the model may also be extended to decisions other than those that apply the cutoff rule.

Additional limitations arise from the experimental test of the normative predictions. We performed the experiment in a controlled environment for theory testing purposes. These controls may limit the extent to which the results can be generalized to predict actual decision strategies in other less controlled environments. Future research may provide insights into such issues by systematically varying the decision environment to incorporate additional task features.

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APPENDIX

A. Derivation of Expected Costs

Expected Cost: CPA—Screening

Inspection of attribute 1. The consumer starts with the first brand incurring processing cost (c_1) and then inspects the next $m - 1$ brands each time incurring a switching cost (b) and processing cost (c_1). Hence, total cost of inspecting Attribute 1 is,

$$C(1) = mc_1 + (m - 1)b. \tag{1}$$

Inspection of attribute i ($i = 2, 3 \dots n$). If the last brand inspected on $i - 1^{\text{th}}$ attribute ($i = 2, 3 \dots n$) passes (probability = p_{i-1}), then that brand will be the first inspected on i^{th} attribute incurring transition cost (a). If the last brand fails on $i - 1^{\text{th}}$ attribute (probability = $1 - p_{i-1}$), then the consumer will switch to another brand for starting inspection of i^{th} attribute incurring transition cost (k). Thus, the expected cost of transition from last brand of $i - 1^{\text{th}}$ to first brand of i^{th} attribute is,

$$p_{i-1}(a) + (1 - p_{i-1})(k). \tag{2}$$

There will be $mp_1p_2 \dots p_{i-1}$ brands (passed on all previous attributes) available for Attribute i inspection, incurring processing and switching cost of (as in Equation 1):

$$mp_1p_2 \dots p_{i-1} c_i + (mp_1p_2 \dots p_{i-1} - 1)b. \tag{3}$$

The total cost of inspecting Attribute i is the sum of Equations 2 and 3:

$$C(i) = p_{i-1}(a) + (1 - p_{i-1})k + mp_1p_2 \dots p_{i-1} c_i + (mp_1p_2 \dots p_{i-1} - 1)b. \tag{4}$$

Total cost. The total expected cost (upon simplifying) is,

$$\begin{aligned}
 EC(CPAS) = C(1) + \sum_{i=2}^n C(i) &= m(EB) + mb(1 + EP) - nb \\
 &+ (n - 1)k - (k - a) \sum_{i=1}^{n-1} p_i
 \end{aligned} \tag{5}$$

$$EB = c_1 + p_1 c_2 + \dots + p_1 p_2 \dots p_{n-1} c_n \text{ and}$$

$$EP = p_1 + p_1 p_2 + \dots + p_1 p_2 \dots p_{n-1}.$$

Expected Cost: CPA—Choice

Inspection of first (n - 1) attributes. When choice (choose the first right brand) is the objective, the expected cost of processing the first n - 1 attributes is the same as for screening (as just noted) and the total cost (obtained by replacing n with n - 1 in Equation 5) is given as,

$$\begin{aligned}
 &= m(EB') + mb(1 + EP') - (n - 1)b + (n - 2)k \\
 &- (k - a) \sum_{i=1}^{n-2} p_i
 \end{aligned} \tag{6}$$

$$EB' = c_1 + p_1 c_2 + p_1 p_2 c_3 + \dots + p_1 p_2 \dots p_{n-2} c_{n-1} \text{ and}$$

$$EP' = p_1 + p_1 p_2 + \dots + p_1 p_2 \dots p_{n-2}.$$

Inspection of attribute n. The cost of switching from attribute n - 1 to attribute n is (from Equation 2):

$$p_{n-1}(a) + (1 - p_{n-1})k = k - (k - a)p_{n-1}. \tag{7}$$

The first brand that passes on the nth attribute will be chosen. Hence, the expected cost of processing attribute n:

$$\begin{aligned}
 &= \sum_{j=1}^m \text{probability that the } n^{\text{th}} \text{ attribute of Brand } j \text{ will be inspected} \times \\
 &\text{cost of attribute } n \text{ inspection (including the brand switching cost)}
 \end{aligned}$$

$$\begin{aligned}
 &= \sum_{j=1}^m \text{probability that brand } (j) \text{ is in the final set (passed on first } n - 1 \\
 &\text{attributes)} \times \text{probability that previous brands (1 to } j - 1) \text{ inspected did} \\
 &\quad \text{not pass on all attributes} \times \text{cost of processing.} \\
 &= p_1 p_2 \dots p_{n-1} [c_n + F(c_n + b) + F^2(c_n + b) + \dots \\
 &\quad + F^{m-1}(c_n + b)] \\
 &= (c_n + b) \left[\prod_{i=1}^{n-1} p_i \right] \left[\frac{1 - F^m}{1 - F} \right] - b \left(\prod_{i=1}^{n-1} p_i \right) \text{ where } F = 1 - \prod_{i=1}^n p_i. \quad (8)
 \end{aligned}$$

Adding Equations 6, 7, and 8, we have:

$$\begin{aligned}
 EC(CPAC) &= m(EB') + mb(1 + EP') - (n - 1)b + (n - 1)k - \\
 (k - a) \sum_{i=1}^{n-1} p_i &+ (c_n + b) \left[\frac{1 - F^m}{1 - F} \right] \prod_{i=1}^{n-1} p_i - b \left(\prod_{i=1}^{n-1} p_i \right). \quad (9)
 \end{aligned}$$

Expected Cost: CPB—Screening

Inspection of brand j (j = 1, 2 . . . m). Consumer starts with Attribute 1 of any brand *j* incurring processing cost (*c*₁). If the brand passes on Attribute 1 (probability = *p*₁), he or she inspects Attribute 2 incurring attribute switching cost (*a*) and processing cost (*c*₂) and so on until the brand fails on an attribute or until all *n* attributes have been inspected. Thus, the expected cost of processing Brand 1 is,

$$\begin{aligned}
 c_1 + p_1(c_2 + a) + p_1 p_2(c_3 + a) + \dots + p_1 p_2 \dots \\
 p_{n-1}(c_n + a) = EB + a(EP). \quad (10)
 \end{aligned}$$

Cost of switching from Brand j - 1 to Brand j. If Brand *j - 1* fails on Attribute 1 (probability = 1 - *p*₁), the consumer will switch to Attribute 1 of Brand *j* incurring brand switching cost, *b*. If brand *j - 1* passes on Attribute 1, he or she would have inspected Attribute 2 of Brand *j - 1*. Hence, switching

to Attribute 1 of Brand j will result in the attribute and brand switching cost, k . Thus, the expected cost of switching from Brand $j - 1$ to Brand j is,

$$(1 - p_1)b + p_1(k) = b + (k - b)p_1. \tag{11}$$

Adding Equation 10 and Equation 11 over m brand inspections and $(m - 1)$ brand transitions yields,

$$EC(CPBS) = m(EB) + ma(EP) + (m - 1)b + (m - 1)p_1(k - b). \tag{12}$$

Expected Cost: CPB—Choice

The first brand will be processed incurring an expected cost of $EB + a(EP)$, as given in Equation 10. If the brand passes on all attributes (probability = $\prod_{i=1}^n p_i$), that brand will be chosen, and the search stops. If it fails on any attribute (probability, $F = 1 - \prod_{i=1}^n p_i$), the consumer will switch to Brand 2, incurring a switching cost of $b + (k - b)p_1$, as given in Equation 11, and a processing cost of $EB + a(EP)$ and so on. Thus, the total expected cost of processing for choice is,

$$[EB + a(EP)] + F[b + (k - b)p_1 + EB + a(EP)] + \dots + F^{m-1}[b + (k - b)p_1 + EB + a(EP)] \tag{13}$$

Simplifying Equation 13, we have:

$$EC(CPBC) = [EB + a(EP) + b + (k - b)p_1] \left[\frac{1 - F^m}{1 - F} \right] - [b + (k - b)p_1]. \tag{14}$$

B. Proofs of Key Analytical Results

Proof of Result 1: Neutral Format ($k = a = b$)—Screening

Substituting a for k and b in Equations 5 and 12, we have:

$$EC(CPAS) = EC(CPBS) = m(EB) + ma(EP) + ma(EP) + (m - 1)a.$$

Proof of Result 2: Neutral Format (k = a = b)—Choice

Substituting *a* for *k* and *b* in Equations 9 and 14 and simplifying

$$EC(CPAC) - EC(CPBC) = \left[m - \frac{1 - F^m}{1 - F} \right] [EB' + a(1 + EP')] +$$

$$a \left[1 - \prod_{i=1}^{n-1} p_i \right] > 0 \text{ because } m = \underbrace{1 + 1 + \dots + 1}_{(m \text{ terms})} > 1 + \underbrace{F + F^2}_{(m \text{ terms})}$$

$$+ \dots + F^{m-1} = \frac{1 - F^m}{1 - F} \text{ for } F < 1.$$

and all other expressions are clearly positive.

Proof of Result 3: Brand Format (k = b > a)—Screening

Substituting *b* for *k* in Equations 5 and 12 and simplifying,

$$EC(CPAS) - EC(CPBS) = m(EP)(b - a) - (b - a) \sum_{i=1}^{n-1} p_i = (b - a)$$

$$\left[m(EP) - \sum_{i=1}^{n-1} p_i \right] > 0 \text{ because } m(EP) - \sum_{i=1}^{n-1} p_i = m(p_1 + p_1 p_2 +$$

$$\dots + p_1 p_2 \dots p_{n-1}) - (p_1 + p_2 + \dots + p_{n-1}) = p_1(m - 1) +$$

$$p_2(m p_1 - 1) + \dots + p_{n-1}(m p_1 p_2 \dots p_{n-2} - 1) > 0 \text{ because } m \prod_{i=1}^j p_j$$

$$> 1 \forall j = 1, 2, \dots, n - 2.$$

Proof of Result 3: Brand Format (k = b > a)—Choice

Substituting *b* for *k* in Equations 9 and 14 and simplifying

$$EC(CPAC) - EC(CPBC) = EB' \left[m - \frac{1 - F^m}{1 - F} \right] + EP'$$

$$\left[mb - \frac{1 - F^m}{1 - F} a \right] - (b - a) \sum_{i=1}^{n-2} p_i + \left[(m + 1) b - (b - a) p_{n-1} -$$

$$a \left[\prod_{i=1}^{n-1} p_i \right] + \left[\frac{1 - F^m}{1 - F} - 1 \right] \left(\prod_{i=1}^{n-1} p_i \right) (b - a) > 0 \text{ because}$$

$$EB' \left[m - \frac{1 - F^m}{1 - F} \right] > 0 \text{ because } EB' > 0 \text{ and } m > \frac{1 - F^m}{1 - F}$$

$$EP' \left[mb - \frac{1 - F^m}{1 - F} a \right] - (b - a) \sum_{i=1}^{n-2} p_i > EP' (mb - ma) -$$

$$(b - a) \sum_{i=1}^{n-2} p_i = (b - a) \left[m(EP') - \sum_{i=1}^{n-2} p_i \right] > 0 \text{ clearly because}$$

$$m(EP') - \sum_{i=1}^{n-2} p_i = m(p_1 + p_1 p_2 + \dots + p_1 p_2 \dots p_{n-2}) - (p_1 +$$

$$p_2 + \dots + p_{n-2}) = p_1(m - 1) + p_2(mp_1 - 1) + \dots +$$

$$p_{n-2}(mp_1 p_2 \dots p_{n-3} - 1) > 0.$$

$$(m + 1)b - (b - a) p_{n-1} - a \prod_{i=1}^{n-1} p_i > a - a \prod_{i=1}^{n-1} p_i + ap_{n-1} =$$

$$a \left(1 - \prod_{i=1}^{n-1} p_i \right) + ap_{n-1} > 0.$$

Proof of Result 4: Attribute Format ($k = a > b$)—Screening

Substituting a for k in Equations 5 and 12 and simplifying:

$$EC(CPBS) - EC(CPAS) = m(a - b)(EP) + b(n - 1) - a(n - 1) + (m - 1)p_1(a - b) = (a - b)[m(EP) - (n - 1) + (m - 1)p_1] > 0$$

because $m(EP) - (n - 1) = (mp_1 - 1) + (mp_1p_2 - 1) + \dots + (mp_1p_2 \dots p_{n-1} - 1) > 0$.

Proofs of Results 5 and 6

These available from the authors.

C. Statistical Procedure for Testing Processing Sequence

Consider the four attributes case. Call them *A*, *B*, *C*, and *D*, and arrange them so that they are hypothesized to be processed in the ascending rank order: *A*(1st), *B*(2nd), *C*(3rd), and *D*(4th). Define x_{ijk} as the actual rank for Subject *k* for the *j*th brand for the attribute with the hypothesized *i*th rank. For instance, if Subject 1 processed attributes of Brand 1 in the following order: *A*(2nd), *B*(1st), *C*(3rd), and *D*(4th), then $x_{111} = 2, x_{211} = 1, x_{311} = 3, x_{411} = 4$. If a subject did not process all attributes, the next highest rank was given to the attributes not processed. For instance, if subject processed only two attributes of Brand 1: *A*(2nd), *B*(1st) and not *C* and *D*, then $x_{111} = 2, x_{211} = 1, x_{311} = 3, x_{411} = 3$. The following steps yield the test statistic.

Step 1. Sum x_{ijk} over all *m* brands for each *i, k* $v_{ik} = \sum_{j=1}^m x_{ijk}$

Step 2. Rank order v_{ik} to yield r_{ik} . Sum r_{ik} over all *s* subjects

$$R_i = \sum_{k=1}^s r_{ik}$$

Step 3. Compute $L = \sum_{i=1}^n i R_i$

$$\text{Step 4. } L^* = \frac{L - E_0(L)}{[\text{Var } L]^{1/2}} = \frac{L - nk(k + 1)^2/4}{[nk^2(k + 1)^2(k - 1)/144]^{1/2}}$$

L is distribution free and *L** is *N*(0, 1) or a *Z* statistic for large samples (Page, 1963).