A Study of Information Search Behavior during the Categorization of New Products

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Consumers are confronted with hundreds of new products each year, yet little is known about how these new products are integrated into existing knowledge structures. Depending on the new products' similarity or dissimilarity to categories stored in memory, consumers' information search may be influenced. In this study, consumers' information-seeking behavior was explored during the categorization of new products that differed in varying degrees from preexisting category expectations. Results suggest that subjects manage the cognitive effort of search by limiting the breadth of search. However, an inverted-U relationship exists between discrepancy and depth of search. Thus, it appears that, at a moderate level of discrepancy, subjects may examine a relevant set of attributes in greater depth rather than search for information on a broad range of attributes. With high discrepancy, however, it appears that subjects try alternative internal strategies rather than search for more information.

Consumers are frequently confronted with new products in the marketplace. How are these new products integrated within consumers' existing knowledge structures? If a product appears consistent with current knowledge structures, consumers may attempt to fit the new product into one of several known categories in that product class. However, the new product may have characteristics associated with several different product categories (e.g., a low-priced luxury car or a minivan). How do consumers deal with a new product that has both similarities and dissimilarities to existing product categories?

Psychologists have studied the influence of discrepant information on a wide array of information-processing variables. Most of these studies assume that all information about the new stimulus is available and that the subjects' problem is one of interpretation and integration of information. Nevertheless, consumers are often exposed to incomplete information on new products—but they also have the option to search for additional information. It is this process of information search that is examined in this article. Specifically, the information-search behavior of consumers is examined when they are categorizing products that differ in varying degrees from preexisting category prototypes.

CONCEPTUAL FOUNDATIONS

Categorization

Rosch (1975) suggests that, to respond to the overwhelming amount and variety of information in their environment, people group objects and events into categories on the basis of perceived similarities and resemblances. The use of categories allows people to structure and simplify their world so that they can function in a complicated environment. Thus, the categorization approach posits that consumers store information in memory around a set of category expectations (Fiske 1981; Rosch 1975; Rosch and Mervis 1975; Rosch, Simpson, and Miller 1976b; Rosch et al. 1976a).

Empirical evidence suggests that the degree to which information is discrepant from category expectations affects information-processing strategies. For instance, the speed and accuracy of classification are greater for representative members of a category than they are for less representative members (Mervis and Rosch 1981; Rips, Shoeben, and Smith 1973). Subjects citing ex-

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amples of the category list representative members earlier than less representative members (Rosch et al. 1976b).

Sujan (1985) studied information processing by experts and novices who were faced with products that matched or mismatched a category label. In a laboratory study, two camera labels—35-mm and 110-instamatic—were either matched or mismatched with a description of a 35-mm or a 110-instamatic camera. For experts, when the label and the camera descriptions matched (or mismatched), the evaluation process appeared to be more category based (or more piecemeal and constructive), faster (or slower) evaluations resulted, fewer (or more) verbalizations related to the product attributes were generated, and more (or fewer) verbalizations related to the product category were evoked. Also, experts attempted to subtype mismatched products; that is, they tried to find a subordinate-level category that was more similar to the product. Novice subjects generally used more category-based processing than experts did for both the match and mismatch conditions.

One aspect of the consumer-information environment suggests an additional avenue for research in this area. Consumers often have incomplete information about new products. For example, assume a consumer needs word-processing capabilities and is in the market for a computer. The consumer is exposed to an ad for a word-processing machine that is like an electric typewriter but also has memory, a limited screen, and spelling checks. When evaluating this discrepant product, will the word-processing machine be compared with electric typewriters or computers, or will the consumer use both categories? When faced with a product that has similarities and dissimilarities to categories stored in memory, how will the consumer's information acquisition be affected? Research in categorization has not yet explored the process of information search during the categorization of stimuli that have varying levels of discrepancy.

The work by Meyers-Levy and Tybout (1989) on incongruity offers some insight into how discrepancy might influence search behavior. They offer three different methods of incongruity (discrepancy) resolution: assimilation ("this product is basically a typewriter"), subtyping ("this product is a word-processing typewriter"), and activation of an alternative schema ("this product is not a typewriter—it is more like a computer"). Although Meyers-Levy and Tybout offer no suggestions as to how these different modes of incongruity resolution might influence information search, each method might lead to a different pattern of search behavior. For example, assimilation may result in little information search because the object is perceived to be consistent with expectations. However, activating an alternative schema may result in more information search because the object must now be compared with information associated with another category.

Information-Search Behavior and the Categorization of Discrepant Stimuli

No empirical or conceptual work exists on information-search behavior during the categorization of discrepant objects. Although a well-developed theory does not exist, the study can be guided by existing research that indirectly addresses the problem of information-search behavior during the categorization of discrepant objects. Existing research suggests that people generally limit the amount of cognitive effort required to complete a task by reaching satisfactory rather than optimal conclusions (Bettman 1979; Newell and Simon 1972). Thus, when asked to categorize new objects, people will not seek all available information: the seeking and processing of information needed to categorize with certainty demands too much cognitive effort.

For instance, suppose that a consumer is trying to categorize a new car as either a luxury or an economy car. If all initial information about the car is consistent with a luxury-car prototype, the consumer may make a categorization judgment with little additional information search. The economic theory of search suggests that when people realize that the object is similar to a known category their search for information should stop because seeking additional information will have little incremental benefit for making a categorization judgment relative to its cost.

However, information search should increase as discrepancy increases to a moderate level. A moderate level of discrepancy is a situation in which most (but not all) of the initial information obtained by the consumer is consistent with a preexisting category prototype, such as a car that has many features associated with a luxury car but also has some features that are usually associated with an economy car. In this situation, initial information does not completely conform to the consumer's expectations for a luxury car. Relative to the previous example of complete consistency with the luxury-car prototype, the benefit of seeking additional information should be greater in this case since additional information may resolve the discrepancy.

What will happen when the level of discrepancy becomes extreme? In this situation, initial information about the object is equally divided between two different categories, such as luxury and economy cars. The prediction regarding information search in this case is unclear. The need for closure, as articulated in the perceptual-integration literature, indicates that consumers need to understand the world around them and give it meaning (e.g., Heimbach and Jacoby 1972). This view of consumers suggests that they strive for a level of certainty in their judgments and adjust their cognitive effort accordingly. Thus, information search and processing should increase monotonically as discrepancy increases from low to very high. On the other hand, the cognitive-effort literature indicates that consumers trade off certainty against effort (e.g., Johnson and Payne 1985). This view suggests that, under high levels of discrepancy, information search and processing effort may not increase even though uncertainty would increase.

Other predictions emanate from the categorization-process literature, which suggests that categorizing new objects requires four stages: (1) primitive categorization, (2) cue search, (3) confirmation check, and (4) confirmation completion (e.g., Bruner 1957). Once again, in our car example, the consumer may judge that a highly discrepant car is not representative of either the luxury or economy categories in the first stage of the process (primitive categorization). Cue search would only confirm this judgment. Thus, information search may decline relative to the moderately discrepant situation. Since any information that is acquired is used only to confirm the initial judgment, time spent processing each piece of information should decline as well.[1] Instead of trying to resolve the discrepancy, consumers may use another strategy, such as subtyping or activating an alternative category.

The conflict-theory literature also suggests that an inverted-U relationship exists between discrepancy and information search (Berlyne 1960). It is proposed that discrepancy evokes conflict and that greater search occurs as conflict moves from low to moderate levels. However, under high levels of conflict, additional information processing yields limited benefits and, therefore, people will use alternative strategies to resolve the conflict. In fact, empirical work by Hendrick, Mills, and Kiesler (1968) on the relationship between conflict and decision time lends indirect support for an inverted-U relationship between discrepancy and information search.

In summary, a variety of theoretical bases do not converge on predictions regarding the relationship between discrepancy and information search during categorization, especially for a high level of discrepancy. The literature that we use to inform our hypotheses is not substantively clear on what should be predicted for high levels of discrepancy. Consistent with the categorization-process and conflict-theory literature, however, we will propose that an inverted-U relationship exists between discrepancy and information search. However, we will examine both linear and nonlinear relationships in the data analysis and interpret the data in light of existing theory to work toward further theoretical development on this substantive problem. McGrath and Brinberg (1983) suggest that there are many paths to knowledge development. Given the current level of conceptual development in this area, we will let the substantive empirical findings inform the conceptual development.

[1]We are grateful to an anonymous reviewer for providing these alternative views regarding the high-discrepancy situation.

HYPOTHESES

Breadth and Depth of Search

The amount of information search and processing can be conceptualized as having two components: breadth and depth. In the consumer domain, breadth of information search and processing refers to the number of different attributes that are acquired or processed. Depth of search and processing refers to the amount of search or processing devoted to each attribute. Thus, when performing categorization tasks, consumers can manage their cognitive effort by manipulating the breadth and/or depth to which information is acquired and processed.

When making judgments, people will generally evoke a limited set of attributes from memory and then use this information (Johnson 1986). Consequently, when faced with discrepant products, consumers may spend more time and effort processing a limited number of attributes rather than seek information on a larger set of attributes. This view predicts that the breadth of search will remain relatively unaffected by discrepancy and that changes in search effort will be reflected in the depth of search. On the other hand, moderately or highly discrepant products may evoke an alternative product category, which would then activate another set of attributes. If this were to occur, both the depth and breadth of search would increase. As discussed earlier, it is predicted that search effort will increase as discrepancy increases to a moderate level. While the relationship is unclear at higher levels of discrepancy, we predict that the breadth and depth of search will decrease relative to moderate levels.

> H1: An inverted-U relationship exists between discrepancy and the breadth and depth of search; that is, at a moderate level of discrepancy, the breadth and depth of search will be greatest.

The overall amount of information requested and the overall time spent searching are direct functions of the breadth and depth of search. Thus, our second hypothesis is as follows.

> H2: An inverted-U relationship exists between discrepancy and the overall amount and time of search; that is, at a moderate level of discrepancy, the overall amount of information requested and the time spent searching will be greatest.

Type of Information Sought

The type of information sought may also change across levels of discrepancy. Once again, in our car example, people may request information about attributes generally associated with luxury or economy cars to categorize a new car. The number of requests closely related to the available categories, in this case luxury and economy cars, will be greatest when the individual consults both categories. At a low level of discrepancy, requests for category-related information should be lowest because the initial information conforms well to one category. It is not clear, however, whether the individual is more likely to consult both categories at a moderate or at a high level of discrepancy. We predict that, at a moderate level of discrepancy, consulting both categories will provide useful information. At high levels of discrepancy, however, consulting both categories will only confirm the discrepancy, so an alternative strategy will be used. Thus, our third hypothesis is as follows.

> H3: An inverted-U relationship is predicted between discrepancy and category-related information; that is, at a moderate level of discrepancy, requests for category-related information will be greatest.

Categorization Uncertainty

At low levels of discrepancy, the object closely conforms to consumers' category expectations; thus, categorization uncertainty should be low. As discrepancy increases, categorization uncertainty may increase as consumers trade off certainty against cognitive effort. As discrepancy increases to very high levels, uncertainty may continue to increase, level off, or decrease depending on how consumers deal with the discrepancy. The perceptual-integration literature suggests that uncertainty will level off. The cognitive-effort literature suggests that uncertainty will continue to increase if the consumer continues to use the same discrepancy-resolving strategy. If the consumer switches to an alternative strategy such as subtyping, however, uncertainty may decrease. Thus, to be consistent with our earlier predictions, we will predict that categorization uncertainty will decrease at high levels of discrepancy relative to moderate levels.

> H4: An inverted-U relationship is predicted between discrepancy and categorization uncertainty; that is, at a moderate level of discrepancy, categorization uncertainty will be greatest.

METHOD

An experiment was conducted in which subjects were asked to categorize three stimuli that had three different levels of discrepancy. The stimulus products were three hypothetical cars that could be categorized as either luxury or economy cars after subjects requested information from a computerized data base. Subjects were given the opportunity to search for as much information about the experimental stimuli as they wanted. The computer recorded all requests for information, which were then analyzed as a function of the product-discrepancy level.

Subjects and Product Class

The sample consisted of 43 undergraduate business students from a major state university who participated in the study as one of the alternatives in fulfilling a course requirement. The product class, automobiles, was selected to achieve four objectives. First, the purchase of an automobile is monetarily, psychologically, and socially important and is associated with relatively high degrees of external search (see, e.g., Punj and Staelin 1983). Second, the purchase of an automobile was relevant to the subjects since most of them would soon be considering or had recently considered the purchase of an automobile. Third, pretests indicated that the subjects' technical knowledge about cars was relatively uniform across the sample. (The most "technical" references made in open-ended pretests concerned the type of transmission, the type of suspension, and the size of the engine.) Thus, knowledge, a potentially important influence on search behavior, should not be a major source of noise in the dependent variables. Finally, pretests indicated that the subject population had similar expectations about luxury and economy cars. This requirement was necessary to create stimuli that could be perceived as discrepant or nondiscrepant with category expectations (for the discrepancy manipulation).[2]

Experimental Design and Independent Variables

This study employed a three-level, within-subject manipulation of the discrepancy factor and a two-level, between-subjects manipulation of the category-type factor. For the between-subjects category-type manipulation, a subject saw either three cars that deviated from the luxury-car category expectations or three cars that deviated from the economy-car category expectations.

The three levels of product discrepancy were manipulated by constructing three hypothetical cars, each with a different degree of product discrepancy. Product discrepancy was created by including both luxury and economy information on different automotive attri-

[2]In pretests, subjects were asked to list characteristics common to vans, economy cars, trucks, and luxury cars. In pretest 1 (n = 20), subjects listed characteristics of vans and economy cars, and in pretest 2 (n = 22), subjects listed characteristics of trucks and luxury cars. Unaided generation of attributes is a rough measure of category structure and provides a basis for choosing among the vehicle categories. The number of common attributes (attributes listed by 50 percent or more of the subjects) and idiosyncratic attributes (attributes listed by 15 percent or less of the subjects) was examined to evaluate the four categories of vehicles. More common attributes were associated with luxury cars (5) and economy cars (4) than were associated with trucks (2) and vans (1). Furthermore, fewer idiosyncratic attributes were associated with luxury cars (10) and economy cars (5) than were associated with trucks (21) and vans (17). Therefore, luxury and economy cars best met our objective of shared category expectations.

butes in the same cars. This product information was then stored in a computer data base. For instance, a plush interior and a large number of options are associated with a luxury car. However, a car with a plush interior but *no* power steering is discrepant.

Each subject judged all three cars: one each in the low-, medium-, and high-discrepancy conditions. To give subjects a point of reference from which to start their search, they were given information on three attributes for each car: safety, air-conditioning, and carpeting.[3] Only a limited amount of information was provided so that additional search would still be necessary. The initial descriptions were created with low, medium, and high levels of discrepancy to parallel the discrepancy level in the three experimental stimuli. The presentation order of the three cars was counterbalanced to minimize presentation-order effects (Greenwald 1976), but subjects could ask for information about any of the three cars in any order that they chose. Thus, the manipulations of category type and discrepancy level result in a crossed and balanced design.

To generate information on the attribute values associated with luxury and economy cars, in pretest 1 (n = 20) and pretest 2 (n = 22), undergraduate students listed those attributes that they perceived as associated with a luxury or an economy car. From these responses, for both the luxury and the economy cars, the most frequently cited attributes were identified. In pretest 3 (n = 22) and pretest 4 (n = 18) subjects were asked to rank order the importance of the attributes in determining whether a car was a luxury or an economy car. This information was used to ensure that the attributes in the computer data base that were given "discrepant" values would be equally important in the judgment task as were the attributes given nondiscrepant values.[4]

Because subjects may have idiosyncratic desires for information, additional attributes were generated from pretests 1–4 and automotive promotional material. Approximately 200 attributes and over 750 synonyms were stored in a computer data base, and this information could be requested by the subjects. Some attributes had no luxury or economy values (e.g., all cars have ashtrays). On the attributes that could vary (e.g., type of tires), the different discrepancy levels were maintained in the data base at levels of 0 percent, 25 percent, and 50 percent. For example, at the 25 percent (moderate) discrepancy level, one out of every four attributes had a value inconsistent with the category type (luxury or economy).

Data Collection Procedures

On arriving at a microcomputer laboratory, the subjects were randomly assigned to one of two conditions: the luxury or economy condition. Up to four subjects were run concurrently. Subjects were seated separately and given a folder that contained all of the necessary exhibits and questionnaires. After the subject was seated before a microcomputer, the cover story was presented: a major (anonymous) car manufacturer was interested in consumers' perceptions of three new unmarketed cars. The purpose of this guise was threefold. First, for the experiment to be successful, the subject could not know that his/her information search pattern was being traced; the cover story deflected attention from the real purpose of the study. Second, the cover story motivated the subject to be involved in the study and to take his/her role seriously. Finally, the use of hypothetical cars was necessary so that subjects could not search internally for brand-specific information.

Next, the subject filled out an initial questionnaire that measured automotive knowledge. The subject then began a warm-up exercise to become familiarized with the experimental procedures and to increase the homogeneity of computer proficiency across subjects. The use of the computer warm-up exercise allows subjects to start the experiment from a similar context (Greenwald 1976). To avoid the possibility that the warm-up

[3]In pretests, consumers ranked 15 attributes with regard to their importance in determining luxury and economy cars. Safety (high/low), air-conditioning (present/absent), and carpeting (present/absent) were ranked as similar in importance in these pretests. For the luxury car, the mean importance was 7.9 for air-conditioning, 8.3 for carpeting, and 9.0 for safety. For the economy car, "lack of extras"—which would include the attributes of air-conditioning and carpeting—was ranked 8.1, while safety was ranked 11.4 in importance. For the low-discrepancy car, all three attributes were either luxury valued (i.e., highest crash-safety level, air-conditioning, and plush carpeting standard) or economy valued (i.e., minimum crash-safety level, no air-conditioning, and plush carpeting optional). For the medium-discrepancy car, one attribute was discrepant (i.e., luxury-based car had plush carpeting optional, and the economy-based car had plush carpeting standard). The high-discrepancy car was the same as the medium-discrepancy car but the crash safety level was average—the safety information favored neither the luxury nor the economy prototype. Thus, in the descriptions, the medium- and high-discrepancy cars were close in their degree of discrepancy, and additional search was required to make an informed judgment of category membership.

[4]The 15 attributes that were rank ordered in importance for the economy car were good gas mileage (1.3), small size (2.7), small engine size (3.7), light weight (4.3), little interior space (6.5), not very luxurious (7.4), few extras (8.1), two-door (8.4), easy to maneuver (8.5), manual transmission (10.5), hatchback (10.5), not very safe (11.4), poor quality of ride (11.9), bucket seats (11.9), and box shaped (12.1). The 15 attributes that were rank ordered in importance for the luxury car were plush interior (3.6), smooth ride (4.8), comfortable (5.3), quiet ride (5.5), sleek body lines (6.1), power accessories (7.7), air-conditioning (7.9), cruise control (8.1), roomy (8.3), carpeting (8.3), deluxe stereo (9.0), safety (9.0), large size (11.7), automatic transmission (11.8), and sunroof (11.9). This rank order of importance was used in the creation of the automotive data base. Care was taken to make sure that different attributes that should covary in a normal car did indeed covary. For example, size, weight, interior head room, and leg room could be considered to be four attributes, but to create stimuli that were realistic, cars were given either all luxury or all economy values on each of the four attributes. The authors also used some degree of extrapolation in creating the data base. For example, smooth ride was operationalized by the type of shock absorbers; easy to maneuver was translated into a small turning radius; quiet ride was translated into noise level, and so on.

exercise would affect the subject's search processes for automotive information, this session involved searching for information about an unrelated topic. The question format in this exercise was exactly the same as the format used in the automotive-categorization task. The subject was instructed to move on to the focal task when s/he felt comfortable using the computer. The subject could, however, repeat the warm-up task as many times as s/he felt was necessary.

After completion of the practice task the subject began the categorization task. The subject first read three short descriptions of the cars and then searched through a computer data base for information until s/he could categorize each experimental stimulus. Subjects were told to "think about what makes a car a luxury or economy car" and that they would be deciding whether each car was a luxury or an economy car. Category-judgment and price-perception measures were taken after the search task. Finally, the subject completed an exit questionnaire and was thanked. The exit questionnaire measured general category expectations, task involvement, task understanding, preferences, and the categorization process. The subject was debriefed at a later time.

Computerized Task

Most laboratory studies of external information-search behavior have relied on the information-display-board (IDB) methodology, which presents information organized in an attribute-by-brand matrix (e.g., Jacoby et al. 1976; Payne 1976). For this study, the IDB methodology was inappropriate because it imposes a well-defined structure on the search task (Brucks 1985). Specifically, this study proposes that existing category expectations will guide the choice of attributes on which to search; thus, providing subjects with attributes would interfere with our ability to assess the influence of stored category expectations on information-search behavior.

Brucks (1985) offers an alternative methodology, a computerized shopping simulation, that does not structure the task by providing attributes. A hidden experimenter responds via a computer to subject-generated requests for attribute information. The methodology employed in this study, the keyword-recognition approach, extends Brucks's work (Ozanne 1988). Here, an artificial intelligence routine responds to subject-generated requests for attribute information. Communication between a human and a computer is based on a few simple ideas. The text is first scanned for keywords. When these keywords are identified, the sentence is transformed according to a rule that has been associated with the keyword. This description captures the fundamental logic behind computer programs that use natural language inputs; however, in practice the procedure is much more complex (see, e.g., Weizenbaum 1966). The greatest obstacle with a natural language program is generating all the possible rules for multiple-keyword sentences. Nevertheless, this keyword-recognition approach becomes feasible when the number of sentence structures is limited to five (e.g., "What type of ____ does brand ____ have?" or "Does brand ____ have ____?") and only one to three keywords are used simultaneously. The subject is still free to generate almost any desired questions. Thus, the keyword-recognition program traces information-search behavior with a semistructured approach that does not cue product-attribute information. A similar approach, called "Search Monitor," was taken by Brucks (1988).

Conceptually, this method and Brucks's (1985, 1988) methods offer the same central advantage: attributes are not cued for the subject. However, the current method and Search Monitor (Brucks 1988) offer some practical advantages over Brucks's (1985) method. Data collection is easier, faster, and cheaper. With the high availability of personal computers, subjects can be run concurrently. Finally, using a computer interface rather than a human interface better ensures homogeneity of the treatment and setting across subjects.

Dependent Variables

Six sets of dependent measures of information search were collected: the breadth of information sought, the depth to which information is processed, the overall amount of search, the overall time spent on search, the type of information requested, and categorization uncertainty. The breadth of search is captured by the *attribute* variable (measured by the total number of different attributes examined). The depth to which information is processed is captured by two measures: *processing* time during search (measured by total search time divided by the total number of attributes) and *search probe* (measured by the total number of multiple questions asked about the same attribute).[5] Overall search is a combination of breadth and depth and is captured by *total search* (measured by the total number of requests made). Overall time spent on search includes the time spent both requesting and thinking about the

[5]Pretests suggested that five different grammatical formats allowed subjects to ask anything that they desired:

1. What is (are) the ____ of car ____?
2. What is the price of ____ for car ____?
3. What type (kind) of ____ does car ____ have?
4. Where is (are) the ____ for car ____?
5. Does car ____ have ____?

Therefore, subjects could ask multiple questions about a single attribute. For example, a subject could ask: Does the car have stereo speakers? What type of speakers are they? and Where are they located? Search probe is a count of the total number of *multiple* requests. If a subject only asked one question about each attribute, search probe would be zero. Each multiple request is counted as one, so in the aforementioned stereo example, search probe would have been two.

TABLE 1

MANIPULATION CHECKS AND PERCEPTUAL MEASURES

Measures	Discrepancy level: Low	Medium	High	F-statistic[a]	Level of significance[b]
Manipulation checks:					
Exposed discrepancy:					
Luxury (n = 19)[c]	.0 (.0)	.38 (.22)	.65 (.18)		
Economy (n = 21)[d]	.0 (.0)	.32 (.12)	.56 (.17)		
Categorization measures:					
Category judgment:					
Luxury (n = 19)	1.68* (.67)	3.68** (1.42)	5.79*** (.92)	66.74	.0001
Economy (n = 21)	5.95* (.97)	4.33** (1.85)	3.19*** (1.75)	13.28	.0001
Price:					
Luxury (n = 19)	12,040* (2,432)	9,692** (2,836)	7,414*** (1.795)	38.49	.0001
Economy (n = 21)	6,516* (1,199)	8,043** (2,916)	9,596*** (2,544)	15.56	.0001

NOTE.—Data are means, with SD in parentheses. Means with the same number of asterisks are not significantly different ($p < .05$).

[a]For luxury, df = 2, 36; for economy, df = 2, 40.

[b]Given the use of a within-subject design, the probability levels were either adjusted by the Greenhouse-Geisser (g) or Huyhn-Feldt epsilon (LaTour and Miniard 1983; Howell 1987). If $g < .75$, then the Greenhouse-Geisser adjustment was used; if $g > .75$, then the Huynh-Feldt adjustment was used. These adjustments either made no difference or led to a more *conservative* test. The probability levels in this table were adjusted by the Huyhn-Feldt epsilon.

[c]For the luxury condition, the exposed discrepancy was significantly different for the three cars: t (medium from zero) = 3.96, 18 df ($p < .001$); t (high from zero) = 8.67, 18 df ($p < .001$); t (high from medium) = 3.81, 18 df ($p < .001$).

[d]For the economy condition, the exposed discrepancy was significantly different for the three cars: t (medium from zero) = 5.82, 20 df ($p < .001$); t (high from zero) = 7.19, 20 df ($p < .001$); t (high from medium) = 4.74, 20 df ($p < .001$).

information, and it is captured by the *time* variable (measured by seconds spent searching). These four sets of dependent measures are computed directly from the computer trace.

The fifth dependent variable is the type of information requested, or category-related information. Category-related requests for each individual subject were measured in the exit questionnaire by having subjects rate attributes (previously identified in a pretest) as being generally associated with luxury and/or economy cars (see Appendix for an explanation).

Finally, in the exit questionnaire, subjects were asked about their perceptions of categorization uncertainty for each car (see Appendix). Subjects also estimated the price of each car. Subjects were not allowed to ask the price of the car since this attribute is so important in determining category membership and would have dominated the effect of most other information.

RESULTS

Experimental Checks

A number of randomization checks were performed to determine whether differences existed between subjects who had been randomly assigned to the luxury or economy conditions. For example, in the United States men are often more familiar with cars than women are, and, therefore, checks for differences on sex and automotive knowledge were made between conditions, but no differences were found ($p > .15$). Checks were also made on the task understanding, task involvement, and the error rate. Again, no differences were found ($p > .15$). Thus, on the variables that were explored, no significant differences existed between subjects in the luxury and economy conditions (see Appendix for explanations of these measures).

Manipulation Check

While the three cars were created with precise levels of discrepancy in the computer data base, subjects could search freely and may not have been exposed to three levels of discrepancy. Therefore, a manipulation check of the actual discrepancy to which subjects were exposed was included. For each subject, the number of discrepant pieces of information seen as a percentage of the total pieces of information collected was calculated for each car. For the low-discrepancy car, the exposed discrepancy is zero for all subjects since no discrepant information was available. In both the economy and luxury conditions, exposed discrepancy for the medium-discrepancy car was significantly greater than zero (i.e., the exposed-discrepancy level for the low-discrepancy car) and was significantly less than the high-discrepancy car ($p < .001$). Means are presented in Table 1. Thus, subjects were exposed to three significantly different levels of product discrepancy; that is, the intended manipulation of product discrepancy was achieved.

Categorization Measures

To add further insight to our understanding of the manipulation of discrepancy, subjects' perceptions of the cars immediately at the conclusion of the information-search task were analyzed as a function of discrepancy level and category type (see Table 1). To provide a measure of category judgment for each car, subjects responded to a seven-point semantic differential scale anchored by "luxury car" on the low end and "economy car" on the high end. This scale was administered immediately after the search task. For both the luxury and economy conditions, discrepancy level had a significant main effect on final category judgments ($p < .001$) and the means for the three cars were all significantly different from one another ($p < .05$). In the luxury condition, the low-discrepancy car was viewed as a luxury car ($\bar{X} = 1.68$), and the medium-discrepancy car was viewed as fairly neutral but leaning toward luxury ($\bar{X} = 3.68$). The high-discrepancy car was perceived as an economy car ($\bar{X} = 5.79$). In the economy condition, the low-discrepancy car was viewed as an economy car ($\bar{X} = 5.95$), and the medium-discrepancy car was viewed as fairly neutral but leaning toward economy ($\bar{X} = 4.33$). The high-discrepancy car was perceived as somewhat luxurious ($\bar{X} = 3.19$).

As a second measure, we asked subjects to estimate the price of each car. The results support the view that, for both the luxury and economy conditions, the estimated prices at each discrepancy level are all significantly different ($p < .01$). In the luxury condition, as product discrepancy increased, price decreased (low, $\bar{X} = \$12,040$; medium, $\bar{X} = \$9,692$; and high, $\bar{X} = \$7,414$). In the economy condition, as product discrepancy increased, price increased (low, $\bar{X} = \$6,516$; medium, $\bar{X} = \$8,043$; and high, $\bar{X} = \$9,596$). These results provide even stronger evidence that the three cars were perceived differently (see Table 1).

Computer Methodology Checks

Several measures were used to determine the viability of the keyword-recognition computer methodology (see the Appendix). A three-item scale (Cronbach's $\alpha = .72$) indicated that subjects understood the task ($\bar{X} = 1.64$, where a low score indicates understanding). A five-item scale (Cronbach's $\alpha = .72$) indicated that subjects had a moderately high level of involvement ($\bar{X} = 1.88$, where a low score indicates involvement).

From the computer trace, the number and type of errors made when subjects requested information in the open-ended format provide a way to evaluate the methodology. Of the total number of requests made, 7.07 percent were not recognized by the computer. Of these errors, 79 percent were answered after the subject retyped or rephrased the question. Thus, only about 1.51 percent of the *total* number of requests went unanswered. If this methodology were used with less complex products, error rates should be even lower.

HYPOTHESIS TESTING

The hypotheses were tested using a 3 (within-subject, discrepancy level) × 2 (between-subjects, category type) ANOVA design.[6] As discussed earlier, although inverted-U relationships were proposed for each of the hypotheses, both linear and nonlinear relationships were tested. Trend analysis was performed to assess the inverted-U relationships. Quadratic relationships were tested with the method recommended by Rosenthal and Rosnow (1984, 1985).

Breadth and Depth of Search

For the relationship between discrepancy and the breadth of information search, the results support that neither a linear nor a nonlinear relationship exists (see Table 2). No significant differences existed in the number of attributes examined across low, moderate, and high levels of discrepancy. However, the effects of discrepancy on the depth of search support a significant inverted-U relationship (see Tables 2 and 3). This relationship was significant for both measures of the depth of search: search probe ($p < .05$) and processing ($p < .025$).

An inverted-U relationship existed between discrepancy and depth of search, yet subjects' breadth of search did not vary significantly. These results suggest that subjects may have managed their cognitive effort by limiting the breadth of their search. Thus, it appears that at moderate levels of discrepancy people spent more time and processing effort analyzing a set of relevant attributes rather than collecting information on a broader range of attributes.

Overall Amount of Search and Time Spent

The overall amount of search and time spent searching is a function of the depth and breadth of search. An inverted-U relationship was predicted between discrepancy and the overall level of search. The results did not support a linear or a nonlinear relationship between discrepancy and the overall amount of search. A significant inverted-U relationship between discrepancy and time spent searching was found ($p < .025$).

[6]Of the 43 subjects who participated in the study, three subjects were dropped prior to the analysis. Two subjects were confused and did not follow basic instructions; a computer malfunction arose with the third subject. No subject correctly guessed the experimenters' hypotheses when asked to explain the purpose of the study in the exit questionnaire. Furthermore, absolutely no mention of product discrepancy or any related concept was made indicating that the subjects were unaware of the study's focus on product discrepancy.

TABLE 2

ANOVA SUMMARY: TESTS OF HYPOTHESIZED MAIN AND INTERACTION EFFECTS FOR CATEGORY TYPE AND DISCREPANCY LEVEL

Dependent[a] measures	Category type effect (df = 1, 38)	Discrepancy level effect (df = 2, 76)	Trend analysis for discrepancy level[b] (df = 1, 76)	Type × level (df = 2, 76)
Information search:				
Breadth:				
Attribute	.04	.86	.29	.95
Depth:				
Search probe	.07	4.20[c,+]	3.96[*]	.25
Processing	.01	6.27[d,+]	12.77[+]	.38
Overall amount of search	.01	2.95[c]	2.24	.83
Overall time spent	.24	3.72[d,*]	7.34[+]	.43
Type of information:				
General category expectations	.02	4.65[c,+]	5.98[+]	1.91
Perceptual measure:				
Categorization uncertainty	1.71	7.55[c,+]	7.93[+]	3.06

NOTE.—Data are F-statistics.
[a]The means and SDs are provided in Table 3.
[b]Trend analysis was performed to assess the inverted-U relationship (quadratic trend) between discrepancy level and information acquisition. The three groups were weighted (−1, 2, −1) in a manner suggested by theory and following procedures suggested by Rosenthal and Rosnow (1984, 1985).
[c]Huyhn-Feldt adjustment (see n. in Table 1), Greenhouse-Geisser epsilon > .75.
[d]Greenhouse-Geisser adjustment (see n. in Table 1), Greenhouse-Geisser epsilon < .75.
[+]$p \leq .025$.
[*]$p \leq .05$.

Type of Information Sought

An inverted-U relationship was predicted between discrepancy and the type of information sought. A trend analysis supported an inverted-U relationship for the category-related variable ($p < .025$); that is, as product discrepancy increases, more category-related requests are made but, at high levels of product discrepancy, these requests decrease. Thus, the highest number of requests for category-related information was at a moderate level of discrepancy.

Categorization Uncertainty

An inverted-U relationship was predicted between discrepancy and categorization uncertainty, and a significant inverted-U relationship was found ($p < .025$). Categorization uncertainty was highest at a moderate level of discrepancy. At a high level of discrepancy, categorization uncertainty decreased.

DISCUSSION AND CONCLUSIONS

The cognitive-effort literature suggests that people manage their cognitive effort by varying the breadth and/or depth of their information search. The results suggest that, in this categorization task, people compared the stimuli across a limited set of attributes retrieved from memory. Thus, people held the breadth of their search constant across the different stimuli. For discrepant stimuli, people increased the depth of search by spending more time and effort processing information on this limited set of attributes rather than looking for information on a wider range of attributes. The highest level of information search and processing effort occurred with the moderate-discrepancy stimuli. Consistent with our predictions, at a moderate level of discrepancy, the benefit of information acquisition is greater than the cost of getting this information; information search is a viable strategy for resolving moderate discrepancy.

For the high-discrepancy stimuli, the results are more consistent with the categorization-process and conflict-theory literature than with the perceptual-integration or cognitive-effort literature. The perceptual-integration literature, which is based on people's need for closure and certainty, predicts that as discrepancy increases information search and processing effort will also continue to increase. But at high discrepancy, search decreased. The cognitive-effort literature, which is based on people trading off certainty against effort, predicts that information search and processing effort may not increase but that uncertainty will increase. At high levels of discrepancy, however, uncertainty decreased. Thus, consistent with the categorization-process and conflict-theory literature, rather than try to resolve the discrepancy through information search, consumers appear to have tried alternative strategies, such as subtyping or activating an alternative category from memory.

In this study, no direct measures of the strategy subjects used to resolve the discrepancy were taken. Some indirect evidence on the information-processing strategy used in this task is yielded by the type of information sought at varying levels of product discrepancy. Requests for information on attributes associated with

TABLE 3

ANOVA RESULTS: CELL MEANS AND PLANNED MEAN COMPARISONS

	Main effects				
	Category type		Discrepancy level		
Dependent measures	Luxury	Economy	Low	Med	High
Information search:					
Breadth:					
Attribute	9.84	10.08	9.60[a]	10.13[a]	10.18[a]
	(3.65)	(3.80)	(4.24)	(4.06)	(4.09)
Depth:					
Search probe	2.37	2.22	1.75[a]	2.68[b]	2.45[b]
	(1.76)	(1.64)	(1.81)	(2.43)	(1.92)
Processing	37.90	38.35	32.41[a]	47.95[b]	34.06[a]
	(7.40)	(15.03)	(10.86)	(32.33)	(12.26)
Overall amount of search	12.25	12.13	11.23[a]	12.80[b]	12.53[a,b]
	(5.12)	(5.10)	(4.98)	(5.52)	(4.72)
Overall time spent	375.33	409.02	313.10[a]	509.35[b]	356.60[a]
	(223.30)	(438.93)	(183.99)	(520.46)	(228.53)
Type of information:					
General category expectations	8.59	8.73	7.88[a]	9.40[b]	8.73[a,b]
	(4.11)	(3.39)	(3.40)	(4.30)	(3.36)
Perceptual measure:					
Categorization uncertainty	7.51	8.29	6.93[a]	8.90[b]	7.93[c]
	(1.65)	(2.07)	(2.77)	(2.50)	(2.84)

NOTE.—Data are means; SDs are reported in parentheses. Means with the same letter are not significantly different ($p > .05$); however, for categorization uncertainty, the high discrepancy level is significantly different from the low and moderate levels ($p = .07$).

general category expectations were most frequent at moderate levels of discrepancy. At high levels, other types of information were sought to resolve the discrepancy. One possible explanation is that, at high levels of discrepancy, consumers seek pieces of information that signal values for a larger number of attributes—such as size and gas mileage. In other words, moving to higher levels of abstraction may be a useful strategy for dealing with product discrepancy. Future research might explore the various strategies that consumers use to resolve discrepancy among product attributes and the conditions under which different strategies are evoked.

A study that directly examines the process of categorizing high-discrepancy stimuli is needed. In a new study, subjects could be exposed to high-discrepancy stimuli and, rather than categorize the stimuli into one of two categories (as was done in the present study), subjects could deal with the discrepancy as they see fit. Analysis of verbal protocols could determine whether subjects are subtyping, activating a category from memory, or forming a new category.

Two limitations of the study should be noted. First, given that the measure of categorization uncertainty was a two-item scale, care should be taken in interpreting these results. An improved measure of categorization uncertainty is needed for future studies. Second, subjects were forced to analyze the experimental products on the basis of attribute information only. The focus on information search required that information on specific attributes for each product be acquired one piece at a time. Thus, this study's design discourages holistic styles of processing that might be prevalent in some real-life product-categorization tasks (Cohen and Basu 1987; Murphy and Medin 1985). Future research might examine how product discrepancy affects holistic category judgment processes, as well as how it affects the use of holistic versus attribute-based approaches.

APPENDIX

Operationalizations of Measures: Scale Items, Method of Computation, Directional Anchors, Interpretation, and Reliability

Type of Information: General Category Expectations. On the basis of pretests, 26 attributes were found to be related to luxury and economy expectations. In the exit questionnaire, the subjects individually rated these attributes as associated with a luxury or an economy car. Next, these rated attributes were compared with the actual attributes requested in the computer trace and summed. The attributes were gas mileage, quality of ride, safety level, length of warranty, style, engine size, price, handling, number of options, size, level of comfort, hatchback, air-conditioning, two-door, bucket seats, vinyl roof, power accessories, four-door, stereo, sunroof, cruise control, carpeting, manual transmission, digital dashboard, reclining seats, and automatic transmission.

Perceptual Measure: Categorization Uncertainty. Two seven-point scale items ("I was never sure whether this car was really a luxury car or economy car" [reversed scaled] and "I knew what my decision would be from the beginning and the additional information just confirmed my initial judgment") ranging from strongly agree to strongly disagree measured categorization uncertainty. Low value indicates certainty.

Categorization Measures: (1) Category Judgment. Category judgment was rated on a seven-point scale anchored by luxury and economy. A low rating indicates a more luxurious car and a high rating suggests a more economical car.

(2) Price. The subject was asked to estimate the price of each car.

Experimental, Computer, and Manipulation Checks: (1) Automotive Knowledge. Seven seven-point scale items assessed automotive knowledge. These items included: I have/do not have necessary information to buy a car; I know/do not know important automotive characteristics for buying a car; I do not/do understand steps in purchasing a car (reverse scaled); I am most knowledgeable/least knowledgeable about buying a car; I am most knowledgeable/least knowledgeable about automotive terminology; I understand/do not understand purchasing procedures; I know/do not know automotive characteristics to compare when buying a car. Low value means that the subject is knowledgeable. Cronbach's α = .82.

(2) Task Involvement. Five seven-point scale items measured task involvement and included: I wanted/did not want to do a good job; I did not care/did care about performance (reverse scaled); the study was enjoyable/unenjoyable; the study was boring/interesting (reverse scaled); I recommend/do not recommend participation. A low value indicates high involvement; α = .72.

(3) Task Understanding. Task understanding was measured by three seven-point scale items: I felt comfortable/uncomfortable on the microcomputer; I did not understand/did understand the computer (reverse scaled); I am very confident/not very confident in using the computer. A low rating suggests high ease of use of the computer; α = .72.

(4) Exposed Discrepancy. This proportional measure was constructed from the computer trace of the search task. For the luxury condition, it is the number of requested luxury attributes divided by the sum of requested luxury and economy attributes (for the economy condition it is one minus this value). This measure captures the amount of discrepancy actually seen by the subject.

[*Received June 1989. Revised May 1991.*]

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