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ABSTRACT

The notion of a consideration set describing a subset of brands from which an individual consumer will select or choose has received considerable attention in the recent marketing literature. This paper develops a rational model of the latent consideration set formation process, characterizing it as an information search in a dynamic setting. An individual consumer will holistically evaluate alternative brands as long as the expected outcome of the search justifies the cost. Hence, consideration set generation is viewed as a categorization process with a cost/benefit screening heuristic. In contrast to previous work using the cost/benefit approach, the operationalization here specifies costs and benefits in the utility domain recognizing various processing phenomena which have been shown to affect information acquisition and computational effort. Given the latent character of the process and its outcome, the validation methodology consists of simulating realistic scenarios and comparing the expansion and contraction of the consideration sets against consumer behavior theory and observation.

Key Words: CONSIDERATION SET, RANDOM UTILITY, SEARCH, CHOICE.
INTRODUCTION

The notion of a consideration set describing a subset of brands from which an individual consumer will select or choose is receiving considerable attention in the current literature. In light of evidence that choice sets are defined prior to choice (see, e.g., Bettman 1987, Payne 1982) and that choice model estimates lack robustness when the subset selection phenomenon is ignored (see, e.g., Ben-Akiva and Lerman 1985, Swait and Ben-Akiva 1986), marketing researchers are demonstrating a serious interest in consideration sets (for a review, see Shocker et. al. 1991). The processes by which they might arise (Hauser and Wernerfelt 1990), their integration into choice models (see, e.g., Roberts and Lattin 1991, Vanhonacker 1993), and the evaluation of brands contingent on the set definition (see, e.g., Simonson et. al. 1993).

Despite differences across authors in terminology and definition, the notion of a consideration set generally refers to the identification of a subset of brands from which a choice will be made. That subset changes from purchase occasion to purchase occasion and from consumer to consumer in composition and in size. Given that choices will be limited to the alternatives in the set, there is substantial managerial interest in how these sets are formed, and in the extent to which formation processes can be influenced. Academics have positioned the consideration set concept within the sequential choice paradigm (Manski 1977), approaching it as a step prior to choice. A number of contemporary research questions arising from this positioning are discussed in Shocker et. al. (1991).

Modeling the consideration set formation process is critical given the impact of the set definition on choice model estimates and predictions and the subsequent effects of model results on managerial decisions and actions. The modeling cannot be validated in a traditional sense, however, because neither the process nor the outcome are observable. The latent character requires the model to be theoretically sound and operationally robust, and to have face validity in light of consumer behavior theory and observation. This requires theoretical grounding of the hypothesized process, and extensive testing of its characteristics in a simulated environment which spans the parameter space of realistic settings. To the extent that the model provides implications consistent with theory and observation its validity is enhanced, and it can then be integrated into a choice model to be further empirically validated on the basis of observed choice outcomes.
Validating the model in two steps is consistent with arguments for treating set formation and choice as different tasks. Behavioral decision theorists have argued that set formation is a judgment task involving an overall (holistic) evaluation of each alternative (see, e.g., Einhorn and Hogarth 1981), whereas choice is a more selective task (e.g., some alternatives may be entirely ignored because of low scores on a single attribute; for a discussion, see Bettman et. al. 1991). During consideration set formation, heuristics are used to sequentially evaluate each alternative with the goal of categorizing it as a feasible or non-feasible option. Choice, on the other hand, uses heuristics to select an alternative, taking advantage of what has been noticed in the prior evaluation. Several studies have investigated the effects of such task differences on resulting information processing and memory (see, e.g., Johnson and Russo 1984, Biehal and Chakravarti 1982, 1983). Additionally, arguments have been raised for separating the two processes in modeling efforts (Ben-Akiva and Boccara 1990) and for exploring the managerial implications of marketing actions on choice set formation and choice processes separately (Nedungadi 1990, Vanhonacker 1993).

Methodologically, it would be difficult to validate a consideration set formation process within a choice model. Choice model fit does not necessarily imply a valid set formation process since multiple process models could provide equally good choice predictions. This is particularly likely, as there might be overlap in the determinants of set formation and choice. Hence, separate validation is necessary to recognize the specific behavioral characteristics of the set formation task and to enhance the power of the validation process.

The objective of this paper is to propose a rational model of choice set generation which is grounded in consumer behavior theory and to validate its operational robustness. Given the latent character of the modeled process, the validation methodology relies on numerical analyses of the process dynamics using many replications over realistic scenarios. If the simulated processes behave consistently with theory and observation, the model's validity is enhanced and it would become a strong candidate for integration in choice models so as to enhance their prescriptive and predictive validity.
CONSIDERATION SET FORMATION

Conceptualization

Consideration set generation is basically a categorization task where some alternatives are classified as choice options and others are not. Because of this characterization, research on consideration set generation has been grounded in the categorization literature (Troya 1984, Nedungadi and Hutchinson 1985, Vanhornacker 1993), some of it relying on goal-derived categorization theory (Barsalou 1983, 1985) to recognize the importance of consumption or usage occasion in the generation process (Shocker et. al. 1991). We will follow this theoretical framing here, and use it as a basis to differentiate the choice task from the consideration set generation task. From an information processing and decision making perspective, this distinction is critical to a conceptual understanding of the phenomenon.

The information processing literature distinguishes between choice and judgment as far as task specificity and diagnosticity of inputs are concerned (for a review, see Alba et. al. 1991). In a choice task focus is on discrimination and little attention is paid to attributes or evaluations that do not aid the discrimination task. Accordingly, choice processing tends to be multidimensional with consumers comparing brands on each dimension in turn and then integrating the results of these comparisons into a single overall score which is used to choose the best brand. In a judgment task, on the other hand, focus is on categorization with no requirement to respond to brands differently if they are largely similar. Hence, in judgment tasks, processing is by alternative rather than attributes. All information about a single brand is reviewed and integrated into an overall (holistic) evaluation before moving on to the next brand. As a categorization process, consideration set formation is clearly a judgment task, implying judgment processing (Bettman et. al. 1991).

Behavioral decision theorists have likewise emphasized a distinction between the decision heuristics used in judgment and choice (see, e.g., Einhorn and Hogarth 1981). A judgment task relies on categorization heuristics given the overall evaluation of alternatives. Choice, on the other hand, relies on discrimination heuristics which take advantage of what has been noticed in the overall evaluation (for a discussion, see Bettman et. al. 1991). Unfortunately for our work, most of the research on decision making strategies and heuristics has focused on choice tasks.

It is insightful to contrast the approaches to consideration set formation suggested in the modeling literature with these observations on information processing and decision making.
heuristics in categorization tasks. Three approaches to conceptualizing latent consideration set generation have emerged. One approach suggests that consideration sets arise from determining whether alternative-specific, unobservable constraints are met. For example, in choosing among different modes of transportation, the family car is a considered alternative if it is available at the time the choice is made. This theory of random constraints, developed in transportation economics by Ben-Akiva and Boccara (1990), argues that the individual's environment gives rise to objective (e.g., attributes of alternatives, individual socio-economic characteristics) and subjective (e.g., attitudes and perceptions) constraints which define the consideration set. Given the unobservable nature of these constraints, they are operationalised in a choice context as latent binary variables whose values are conditional on deterministic proxies (e.g., the number of licensed drivers in the family) and a random disturbance. Although conceptually intriguing as a means of integrating external constraints into the choice set generation process, this approach largely treats situational constraints as exogenously specified functions without explicitly recognizing the consideration set generation process and its determinants.

A second approach relies on screening procedures individuals use because of limited information processing capabilities. These screening heuristics have been studied primarily in the context of choice, without independent consideration of categorization. Categorization and selection are viewed as sequential, hierarchical processes driven by identical, choice-type decision making heuristics. Simon's (1955) satisficing model, Tversky's (1972) Elimination-by-Aspects model, and the lexicographic model are prime examples (for an extensive review and discussion, see Bettman et. al. 1991). These models view both the categorization task and the choice task as consisting of selective processing on an attribute by attribute basis not recognising the distinctive features of judgment processing inherent in consideration set generation.

A third approach views consideration set generation as a dynamic process of information search involving costs. The idea is that an individual is willing to bear the cost of search if expectations about the outcome of the search are high. Consideration set generation is viewed as a process of balancing costs and benefits (see, e.g., Meyer 1979, Richardson 1982, Hauser and Wernerfelt 1990, Roberts and Lattin 1991, Vanhonacker 1993). There is extensive support for such a tradeoff heuristic in the decision making literature (Beach and Mitchell 1978, Johnson and Payne 1985, Klayman 1983, Russo and Dosher 1983, Shugan 1980). As a search process where brands are evaluated sequentially, the approach enables differentiation between consideration set generation and choice. Judgment processing in the overall evaluation of each brand would make the approach consistent with information processing theory. Furthermore, the tradeoff heuristic applied in the comparison of overall
evaluations of each alternative is behaviorally quite different from the utility maximizing approach commonly used in choice models (Ben-Akiva and Boccara 1990). Because of its empirical and theoretical support in the consumer behavior literature, we will adopt this approach and operationalise choice set generation as a dynamic information search problem. Before operationalising the process, some characteristics of the tradeoff heuristic need to be discussed.

**Categorization Heuristic**

Previous attempts at cost/benefit modeling of consideration set generation in the marketing literature have evaluated benefits in the utility domain recognising an evaluative component in the categorisation task. (Hauser and Wernerfelt 1990, Roberts and Lattin 1991). This approach is also adopted here because of its theoretical support. As a measure of an individual's relative preferences, the utility concept is nothing more than a holistic judgment of subjective value, moral worth, or psychic satisfaction provided by one alternative relative to another (Fishburn 1988). Furthermore, the utility approach to benefit assessment is entirely consistent with the discrete choice modeling literature where utility maximization has been the dominant choice rule (Ben-Akiva and Lerman 1985). And given that choice is the ultimate objective in the second stage, benefits in the first stage should be evaluated in that light.

The handling of search costs in the modeling literature has been less satisfactory. Primarily, search costs have been viewed as independent from the utility evaluations of the alternatives, and have been incorporated in models as endogenously estimated constants (see, e.g., Roberts and Lattin 1991). This approach is surprising in light of work on cognitive efforts involved in decision making (see, e.g., Bettman et. al. 1991) and operationalisations of these efforts (e.g., Shugan 1980). We briefly review that literature to provide a theoretical basis for our operationalisation of decision costs.

Costs capture both the cognitive effort to acquire the knowledge and the cognitive effort to process it (Bettman et. al. 1991). Acquisition effort has been studied primarily in the framework of competing decision making strategies with special focus on external search for information versus memory recall of information (Lynch and Snell 1982). Nedungadi (1990) points out that in a grocery shopping setting, the environment we are considering, consideration set generation might be stimulus-based because of the physical presence of the brands on the shelf. Alba et. al. (1991) argue, however, that very few consideration set generation decisions are purely stimulus based. They argue that external information search is limited (if it occurs at all) and that memory plays a crucial role. First, the external stimulus
environment in a grocery store is so complex that, in addition to recognition processes, recall about product categories and brands will be important. Second, even if consumers look at a display of a product category, memory factors will influence the ease with which specific brands "catch the eye" and enter into the consideration set. Third, motivation levels are too low and time too scarce for consumers to scan all brands displayed (see, e.g., Park, Iyer, and Smith 1989). Because of this consumers might believe they already possess the information necessary to perform the task without having to engage into external search of the physically available brand and attribute information. Consistent with these theoretical arguments, Dickson and Sawyer (1986) and Hoyer (1984) report low levels of external search in grocery shopping. This would suggest that information acquisition for most frequently purchased items is largely a memory recall task. Accordingly, in modeling the purchase of such items, the cognitive effort in external information search and in memory encoding incurred when learning about the brands and the product category can be considered a sunk cost and we can limit ourselves to the memory retrieval cost in evaluating the categorization heuristic.

Based on memory research (for a review, see Alba et. al 1991), the memory retrieval cost will be a function of how good the individual's memory is, the framing of the recall task (i.e., the presence of retrieval cues which trigger or facilitate recall), and individual preferences (i.e., preferred brands are recalled more easily). Individual differences in memory capability need not be formally recognized in a modeling attempt since they would affect all brands equally, thus adding a constant factor to the acquisition cost of each evaluated brand. Such factors would potentially influence the stopping rule of the search process -- indeed, consumer behavior research has indicated that smaller consideration sets arise when information has to be recalled from memory -- but would not have a differential impact on the information acquisition cost across brands. Since external retrieval cues and brand attitudes do have a differential impact on decision costs, in contrast, it will be important to recognize them when modeling the categorization process.

Apart from the acquisition cost, there is also the processing cost pertaining to the ease with which information is comprehended and used (Russo et. al. 1975). A great deal of conceptual work has been done on information processing and on the limiting heuristics individuals use to simplify processing and, hence, limit cognitive effort (for a review, see Bettman et. al. 1991). Key factors that have been identified in this respect are individual characteristics (e.g., expertise, familiarity, and motivation), task characteristics (e.g., similarity of alternatives, judgment versus choice), and social context characteristics (i.e., the extent to which the individual has to justify the decision outcome to others). Although most research has been done in relation to choice tasks, these findings and observations are relevant to a
judgment task such as the one inherent in consideration set generation since brand evaluations are done in reference to an ultimate choice act.

In sum, a decision cost measure should recognize the possible impact of task, individual, and social context factors. The consideration set formation process involves a judgment task which, as discussed above, implies an overall evaluation of each brand, largely in terms of information recalled from memory. External cues such as physical presence at the time of the holistic evaluation will reduce retrieval cost conditional, of course, on brand familiarity and recognition. Complexity of the brands will increase the cognitive effort and, hence, processing costs needed to arrive at the overall brand evaluations, conditional on consumer expertise. A substantial part of those costs, however, may have been incurred when the alternatives were encoded in memory. To the extent that an overall judgment is recalled, processing effort will only be affected by differences in the aggregate scores across brands. Brand preferences are a critical determinant of evaluation costs because of their impact on speed of recall. Motivation and a desire to make a "correct" judgment ("correct" being defined as one that can be justified and defended to others) must also be incorporated to recognize their impacts on processing effort in the judgment task.

A question arises as to whether we can parsimoniously operationalise the cost/benefit heuristic while simultaneously recognizing these consumer behavior phenomena and limitations on the commonly available information in a non-experimental brand selection context. The managerial objective of enhancing discrete brand choice models with a consideration set generation component becomes practically feasible only if the phenomenon can be incorporated without overly stringent data requirements. Such an operationalisation is introduced next.

**Operationalisation**

The consideration set is defined deterministically as the outcome of a rational process in relation to a specific choice decision. The brands considered are identified using a sequential sampling process balancing benefit, measured as consumption utility, and evaluation cost. The individual consumer will assess the incremental benefit which could be gained from considering the brand in addition to those already selected for consideration. If the incremental benefit is judged to be larger than the cost which would be incurred in having to evaluate an additional brand, the brand will be considered also. Specifically, a brand will be added (deleted) to the consideration set if the expected maximum utility of choosing from (n+1) brands minus the expected maximum utility of choosing from n brands exceeds (does
not exceed) the additional cost of evaluating this additional brand. Algebraically, this tradeoff heuristic can be stated as: the \((n+1)\)th brand is added if

\[
E[\max(n+1)] - E[\max(n)] > d_{n+1}
\]  

(1)

where \(E\) denotes the expectations operator, \(\max(\cdot)\) denotes the maximum utility which could be derived from choosing among \(n\) brands, and \(d_{n+1}\) denotes the cost of evaluating the \((n+1)\)th brand given that \(n\) brands are already in the consideration set. Using similar arguments, dropping a brand from consideration is a result of the reverse inequality.

Evaluating the costs and benefits in reference to a specific choice decision justifies an operationalisation of both elements in the utility domain as most discrete choice models rely on the utility maximization choice rule (Ben-Akiva and Lerman 1985). Accordingly, the same random utility framework commonly underlying choice models is adopted to operationalise the heuristic governing categorization in consideration set generation. Besides being consistent with the ultimate objective of the sequential tasks of categorization and choice, the random utility framework enables the integration of the consumer behavior phenomena discussed above and provides a convenient framework to model the integration of consideration set formation and choice in the future.

In operationalizing the process, two issues have to be addressed. First, both the left and right sides of the inequality have to be operationalized in the utility domain. Second, the sequence of brand consideration has to be determined. We will rely on the assumptions typical in random utility theory. Specifically, the individual consumer has a utility towards each of the \(m\) brands in the universal set of all brands available in the market which consists of both a deterministic component and a random component. Stated algebraically, the utility that an individual consumer attaches to brand \(j\) equals

\[
U_j = V_j + \mu_j \quad \text{for } j = 1, 2, \ldots, m
\]

(2)

where \(V_j\) describes the deterministic utility component, and \(\mu_j\) describes the random utility component (or disturbance, Ben-Akiva and Lerman 1985). The \(\mu\)'s contain all variables which affect utility but which are not observed. Following McFadden (1974), the random utility component is assumed to be independent and identically distributed (i.i.d.) across all brands according to a Type 1 Extreme Value distribution (see Johnson and Kotz (1970), Chapter 21 for a description of this distribution). This particular distribution together with the
The i.i.d. assumption allows McFadden (1974) to derive the parsimonious multinomial logit choice model commonly used in marketing.

The operationalisation of the incremental benefit, the left side of the inequality (1), is implied by the common assumptions of the random utility model. Specifically, if the random utility components \( u_i \) in \( V_j \) are i.i.d. according to a Type - 1 Extreme Value distribution, then (Ben-Akiva and Lerman 1985)

\[
E[\max(n+1)] - E[\max(n)] = \ln \frac{\sum_{j=1}^{n+1} \exp(V_j)}{\sum_{j=1}^{n} \exp(V_j)}
\]

This operationalisation is identical to the one used by Roberts and Lattin (1991). It is interesting to note that the incremental benefit expression equals the log of the odds ratio of selecting any brand from a set of size \( n \) versus selecting it from a set of size \( n+1 \), given the selection probability is defined in a multinomial logit sense (McFadden 1974). In other words, the incremental benefit provided by one brand is a monotone function of the multinomial logit probability of selecting that brand from the smaller set.

Operationalising the decision cost is less straightforward. As discussed above, that cost covers two aspects: the cognitive effort in acquiring the information and the cognitive effort in processing it. The determinants of those components cover task characteristics, individual characteristics, and social context characteristics. A specific measure of the mental cost in comparing two brands with the objective of selecting one was proposed by Shugan (1980). Although not without criticism (see, e.g., Payne 1982), the measure is used as a starting point here because of its parsimony and conceptual fit with the tradeoff heuristic in the consideration set formation process. The specific operationalisation of the decision cost developed here positions Shugan's (1980) measure in the utility domain and extends it by integrating some of the consumer behavior phenomena absent in the original formulation but very much part of the cognitive effort in the categorization task.

Shugan (1980) argues that the cost of evaluating two brands with the objective of selecting one is directly proportional to both the complexity of the comparison and the confidence at which the choice decision must be made, and inversely related to the difference in preference between the brands. Given that choice is viewed as the objective, his measure
relies on the perceptual framework of contingent decision making with cognitive processing effort being directly proportional to an attribute-by-attribute comparison task (Bettman et al. 1991). As discussed above, consideration set generation is a categorization task with judgment-type processing which implies holistic (overall) evaluation of each alternative in sequence. The comparison is done once an overall score has been arrived at for each alternative, which requires cognitive effort to be related to the difference in those overall scores. Hence, Shugan's measure will have to be adapted to the specific task involved in consideration set generation.

Examining the measure further, we see that the inverse relationship with preference is consistent with research on memory recall suggesting that memory retrieval, and hence information acquisition effort, is easier for preferred brands. Furthermore, by integrating the level of confidence at which the choice must be made, the measure captures elements of motivation as well as social context. If the individual feels that the decision will have to be justified to others, one could argue that the confidence will be affected. Despite its simplicity, therefore, Shugan's (1980) measure does integrate important aspects of decision making costs discussed in the consumer behavior literature. Other aspects, such as external cues aiding memory recall, and individual characteristics affecting processing and recall are missing. We will address these and some others specific to the sequential search task hereafter. First, and consistent with the above discussion, we adapt Shugan's (1980) original measure by specifying it in the utility domain to capture the task specificity and to discuss some operational constraints of the original form given traditional random utility assumptions.

The potential cost of comparing brands \( j \) and \( k \), \( f_p \), operationalised in the utility domain equals

\[
f_p = \frac{\text{Var}(U_j) + \text{Var}(U_k) - 2 \text{Cov}(U_j, U_k)}{(1 - \alpha)(E(U_j) - E(U_k))^2}
\]

(3)

where \( U_j \) and \( U_k \) are the utilities of the two brands (as in expression (2)), and \( \alpha \) denotes the level of confidence at which the selection between the two brands must be made (Shugan 1980). The numerator captures the relative complexity of the brands which is measured by the variance of the difference in utility between the two brands (i.e., \( \text{Var}(U_j - U_k) \)). The denominator captures the complement of confidence, the \((1-\alpha)\) component, and the preference difference between the two brands, which is measured by the squared difference in
mean utility. Accordingly, both the complexity and the preference difference are defined in a compensatory way relying on base utilities. This specification is consistent with the judgment task in the categorization process as discussed above.

With the utility functions and the distributional assumptions of their random components as defined in relation to (2), the operationalization of the decision cost in (3) becomes

$$f_P = \frac{2\beta}{(1-\alpha)(V_j - V_k)^2}$$

where $\beta$ denotes the constant variance parameter of the Type-1 Extreme Value distribution. Note that because of the i.i.d. assumption with respect to the random utility components, the covariance term in the numerator of (3) equals zero and, hence, drops out of the expression. As Shugan considers the costs of each pairwise comparison as additive, the decision cost of evaluating the $(n+1)^{th}$ brand, given $n$ brands in the consideration set, becomes the sum of the pairwise evaluation costs. Accordingly, the operationalization of $d_{n+1}$ would become

$$d_{n+1} = \frac{2\beta}{(1-\alpha) \sum_{j=0}^{n-1} \frac{1}{(V_j - V_{n+1})^2}}$$

(4)

where the summation sign captures the sum of all pairwise comparisons involved in the sequential evaluation process.

Expression (4) captures Shugan’s (1980) "cost of thinking" using the random utility assumptions postulated above. Two operational observations are in order. First, the measure assumes that the deterministic utility components of the various brands are different, otherwise the measure goes to infinity. The chance of that occurring is rather limited, however, with the utility functions that have been specified and estimated empirically in the choice modeling literature. Second, because of the random utility assumptions, the concept of complexity originally captured in the numerator of the measure has been reduced to the constant variance parameter of the Type-1 Extreme Value distribution. We cannot assume that the cognitive processing effort in the evaluation and comparison of the overall utility for each alternative will be confined to the unobservable component. Differences in observed components (i.e., the deterministic utility component) need to be considered as well. To restore the complexity component, we suggest incorporating the sample variance of the deterministic utility components. A side benefit of integrating this measure into the decision
cost in (4) is that the scale invariance property, not present in (4) but part of the original measure, has been restored.

With respect to the behavioral characteristics of the categorization task, the presence (or absence) of external cues which aid memory recall need to be discussed and integrated. Since judgments about frequently-purchased, low-priced consumer goods will be largely memory based, the tradeoff heuristic needs to recognize elements which facilitate memory recall. Based on memory research in consumer behavior, a number of those external cues were discussed above. However, apart from the nature of the physical presence of some alternatives, other cues would generally not be known in a typical environment where choice models are estimated and used. For example, in typical supermarket scanner data, the known external cues are limited to in-store cues such as special displays (e.g., end-of-aisle), physical availability, amount of shelf space allocated to various brands, and in-store promotion (e.g., special announcement). But these variables are usually specified in the utility function. Hence, by adopting the utility framework, we have inherently integrated those external cues. Other external cues facilitating recall which are not commonly available could then be viewed as being part of the random utility component.

Some idiosyncratic factors which mitigate memory retrieval are more difficult to integrate. Brand preferences are captured by the utility notion itself. Familiarity, which aids recognition given external cues (Alba et. al. 1991), could be captured by specifying a purchase feedback effect in the utility function. This would operationalize familiarity as the number of historical purchase experiences. The so-called "loyalty" measure suggested by Guadagni and Little (1983) and commonly specified as a deterministic utility component in multinomial logit choice models, is precisely such a measure. The individual characteristics which have been discussed as affecting cognitive effort in decision making (and, hence, decision cost in the tradeoff heuristic) and which are more difficult to integrate are strength of memory and expertise (defined as the ability to perform product-related tasks successfully, Alba and Hutchinson 1987). Those characteristics are likely to affect cognitive effort in the same way across all brands. They impact on the decision cost threshold against which incremental benefits are evaluated, therefore affecting the stopping rule of the categorization process. However, strength of memory and expertise invalidate neither the process nor the sequence in which brands will be considered for inclusion or not. Ignoring these factors because of lack of observation might well lead to an overprediction of the size of consideration sets for experts and an underprediction of the size for individuals with excellent memories. At the individual level, this is a potential weakness of the process model developed here. At the aggregate level, on the other hand, and assuming that these idiosyncratic tendencies are symmetrically distributed across the population, their effects will wash out. Hence, given that our
consideration set generation model is developed with the objective of ultimately integrating it into a choice model and given that those models are generally estimated across individuals, the adverse impact of not explicitly incorporating those tendencies will be limited.

Before the decision making cost can be fully operationalised, one additional issue related to the dynamic and recurring nature of the search has to be considered. Since the consideration set generation process is a sequential search process, multiple comparisons, some involving the same brands, will be made each time a new set is formed. The categorization implies pairwise comparisons between all brands, hence, the overall evaluation of a brand will recur in all the pairwise comparisons involving that brand. It is reasonable to expect that the cognitive processing effort to arrive at that evaluation will decline over multiple comparisons, either because of processing economies (i.e., the individual gets better at doing the judgment processing as he becomes more comfortable and adapts to the task) or lack of effort (i.e., fatigue is setting in because of the repetitive nature of the sequential judgment processing). Johnson et al. (1990) argue for a sequence of adaptation followed by fatigue in judgment tasks. Although both would lead to reduced cognitive effort, adaptation and fatigue could affect the categorization task in different ways. Where adaptation would lead to improved and consistent judgments (and, hence, enhance the rational character of the search process), fatigue would lead to systematic changes because of simplified judgments or careless judgments. Simplification would result in reduced discrimination among similar brands, where carelessness would increase error variances in sequential judgments. Both of these could affect the incremental benefit evaluation in the tradeoff heuristic, thus leading to systematic changes in consideration sets.

With the overall evaluation of each brand operationalised in the utility domain, one could argue that simplification would lead to less variance in the deterministic component of utility across brands where carelessness would lead to increased variance in the random utility component. The tradeoff heuristic adopted here is more influenced by the former than the latter. In order then to integrate the simplification effects arising from fatigue, one needs to postulate what kind of simplification might be adopted and how it would affect the brand utilities. One possibility is that individuals anchor their judgments in the past. Specifically, some form of inertia might set in where brands which have been considered before are being viewed increasingly in a better light. Very much like the re-evaluation of brands in reducing postdecision dissonance (Festinger 1957), the individual might simply adjust utility evaluations upward in function of how long the corresponding brands have been in consideration. The fatigue effect will be integrated precisely in this way. Clearly, more work can be done here as simplification strategies in sequential judgment tasks (as opposed to choice tasks) are not well documented in the consumer behavior literature. We do believe, nevertheless, that the utility
adjustments suggested here capture in a descriptive sense the essence of the impact of the consumer behavior phenomena.

In sum, the sequential nature of the search process will, on one hand, lead to utility adjustments reflecting inertia with respect to brands previously considered and, on the other hand, lead to a reduction in decision making costs. The latter are operationalised here using an exponentially declining cost reduction factor. Hence, no specific assumptions are made about the nature of the learning effects. Also, no distinction is made between decision cost reduction as the result of actual learning (real search economies) and decision cost reduction as a manifestation of reduced effort because of fatigue. The proposed cost reduction factor equals \(1/\exp(\delta S)\) where \(S\) denotes the number of times the consideration set is changed throughout the process of sequential search. As will be discussed shortly, each comparison in the process leads to either an add or a drop decision. Whichever decision is made, the set changes in composition and the incremental benefits of all alternatives change. The evaluation process then restarts and continues until no further changes occur. Variable \(S\) captures the number of restarts of the evaluation process given specific utilities at one point in time. As one would expect, the number of restarts is positively related to the size of the universal set but not necessarily to the size of the consideration set.

Moreover, the full operationalisation of the decision cost \(d_{n+1}\) then becomes

\[
d_{n+1} = \frac{2\beta (1/m) \sum_{j=1}^{\infty} (V_j - \bar{V})^2}{(1 - \alpha \exp(\delta S)) \sum_{j \neq n+1} (V_j - V_{n+1})^2}
\]

(5)

where \(\bar{V}\) denotes the sample mean of the deterministic utility components, and where the deterministic utility of the brands belonging to the consideration set are adjusted by an \(S\)-shaped factor going from \(\gamma \geq 1\) (i.e., the instantaneous adjustment upon entering the consideration set) up to an asymptote of \(2 \gamma\) as a function of the time the brand has been in the set. With this expression, the cost/benefit heuristic has now been fully operationalised. In order to capture the process completely, the search sequence needs to be defined, which is discussed next.

**Sequence of Search**

A number of different mechanisms can be envisioned defining the order in which brands will be evaluated either for entry into or exit from the consideration set. Shugan (1980) suggests
the relative magnitude of the decision costs, commencing with the least costly. Roberts and Lattin (1991) use the relative magnitude of the brand utilities, commencing with the brand with the highest utility. Following information economics, the optimal search sequence (with optimal defined in terms of maximum expected return) over the brands with their uncertain utilities would be defined by the net gain (i.e., expected benefit minus cost) per probability of realizing that gain (Weitzman 1979). In each of these suggested search strategies, one starts from an empty set and builds up to a consideration set at every choice occasion. This seems somewhat awkward in a behavioral context. As discussed above, for example, there is likely to be some inertia in sequential consideration set generation giving rise to asymmetries in entry to and exit from the set. It would seem more reasonable to assume that the individual starts with the consideration set last used (i.e., the historical consideration set), and drop or add brands from there. This is the process we propose, with the sequence of adding and dropping determined by the magnitude of the incremental benefit (i.e., the left side of the tradeoff heuristic in (1)).

Specifically, it is assumed that at time \( t \) (i.e., the current choice occasion), the process starts with the historical consideration set of time \( (t-1) \) (i.e., the previous choice occasion); that is, we start with a consideration set of size \( n \), where \( n \leq m \). All other \( (m-n) \) brands are candidates to enter the consideration set at time \( t \); all \( n \) brands in the consideration set at \( (t-1) \) are candidates to be dropped. The sequence of adding and/or dropping is determined as follows: For each of the \( (m-n) \) brands not currently in the consideration set, the incremental benefit of adding this brand to the set configuration of \( (t-1) \) is computed. The first brand to be considered for inclusion is the one with the largest incremental benefit. All others will be considered in descending order of incremental benefit. For the \( n \) brands already in the consideration set, we first compute the incremental benefit that would be lost if the brand were dropped. This value is then subtracted from the maximum incremental benefit across all brands (irrespective of whether or not they belonged to the consideration set at time \( (t-1) \)). The first brand to be considered for deletion is the one with the largest difference, as this reflects low benefit relative to another member of the existing or potential set. All other \( (n-1) \) brands will be considered in descending order of this difference. To determine whether an add or a drop decision will be made first, the incremental benefits for the potential entrants are merged with the differences of the potential departures and their relative magnitudes determine the overall ordering mechanism. Hence, if the incremental benefit, given brand utilities at time \( t \) and the consideration set configuration of \( (t-1) \), is largest for a brand not yet in the consideration set, that brand will be considered first. If the largest incremental benefit is associated with a brand already in the consideration set at time \( (t-1) \), then that brand will not be considered for removal until the last step of the overall sequence. In essence, the ordering mechanism is driven by potential gains and losses given the utility values of all brands at time.
t. With this search sequence, the rational consideration set generation process has been operationalised completely.

NUMERICAL VALIDATION

In general, model validation consists of face validity, statistical validity, and use validity (Naert and Leeflang 1978). Statistical validation of the consideration set generation model developed above is not possible because of its latent character. As neither the process nor the outcome can be observed the parameters of the process model cannot be estimated, thereby preventing traditional reliability and goodness-of-fit assessment. Use validity relates to the intended use of the model. As the ultimate objective is to integrate the consideration set generation model into a choice model to enhance the validity of the latter, use validation here refers to validation of the choice model with the process model integrated. As we focus in this paper on consideration set generation specifically, we will leave this assessment for future research. Furthermore, the face validity of the generation process itself needs to be established before meaningful use validation should be pursued. Our focus here is precisely on face validity, which is the main validation requirement for descriptive-type models such as the one proposed (Lilien et. al. 1992, p. 594).

Massy (1971) describes four areas for face validity: model structure, estimation, information contribution, and interpretation of results. Because of the latent character of the consideration set generation process, we are confined to the areas of model structure and interpretation of results. Both will be assessed here numerically. Face validity of the model structure refers to the robustness of the model. Robustness is assessed with respect to consideration set sizes as a function of simulated utility distributions across brands and parameter values. The objective is to see if the model gives rise to consideration set sizes consistent with those which have been obtained in the consumer behavior literature. The interpretation of results is assessed with respect to characteristics of expansion and contraction of the set and their consistency with consumer behavior theory and observation. The objective here is to see if the set sizes change in the direction predicted by theory and observation.

The numerical environment was constructed around simulated utility distributions and controlled parameter values. The simulated utility distributions describe the deterministic utility components across the brands available in the market. As shown in (2), apart from a random component, they capture different patterns of preference across brands. Five different patterns were considered: three symmetric and two asymmetric. The symmetric patterns
differ in their variances: one unimodal pattern with brand preferences concentrated around the midpoint of the utility scale, one rectangular pattern with brand preferences distributed equally over the utility scale, and one polarized pattern with brand preferences concentrated towards the endpoints of the utility scale. The two asymmetric patterns consist of a left-skewed distribution and a right-skewed distribution of brand preferences over the same utility scale. Together, these five patterns span a wide range of possible preference distributions at the individual consumer level. They enable a comprehensive test of the operational robustness of the model.

Given that the utility functions in (2) are defined up to an additive constant and that the tradeoff heuristic is invariant under such a transformation, we can limit the deterministic utility to a range from zero to one without any loss of generality. Accordingly, the utility values for the five patterns were drawn from corresponding Beta-distributions. Independent draws out of each of these distributions constitute the replications over which the robustness of the model was assessed.

The consideration set generation model has three parameters: $\delta$ which measures the exponential decline in decision making costs over repeated evaluations, $\gamma$ which captures the S-shaped utility adjustment for brands already belonging to the consideration set, and $\alpha$ which measures the level of confidence at which the individual wishes to make the decision. The first two parameters are descriptive. From the model development discussed above, it is clear that they are not directly interpretable but only capture degree of change in a behaviorally-recognized, inherent dynamic of the categorization heuristic. In contrast, the confidence parameter $\alpha$ is more explanatory in nature and has a direct behavioral interpretation. The absolute magnitude of that parameter measures, in a statistical hypothesis testing sense, the degree of confidence. For the descriptive parameters, only relative magnitudes are interpretable. Furthermore, as $\delta$ and $\gamma$ have no implicit upperbound, it is difficult to justify apriori specific numerical values for them. Consistent with the objective of robustness, we decided to select extreme values and view the corresponding scenarios as points of reference.

For the exponential decline parameter, $\delta$, we considered values of 1 and 3. These values imply "learning rates" of, respectively, 37% and 7%. In other words, with each new evaluation following a change in the tentative consideration set, the decision making cost would be 37% or 7% of the previous level. These rates are steep implying that cognitive processing effort will decline rapidly over successive evaluations. This seems justified given that the acquisition cost of memory-based information is a sunk cost after the first iteration and given the general lack of motivation and time in grocery shopping behavior (Park et. al. 1989). For the utility adjustment parameter $\gamma$, we considered values of 1 and 4. For $\gamma = 1$,
there is no instantaneous utility adjustment when a brand enters the consideration set, but the brand's utility adjusts upwards to a maximum of twice its current value as the length of stay in the consideration set increases over time. For \( \gamma = 4 \) we have extreme inertia, with an instantaneous adjustment of four times the brand's current utility value, which then increases over time with the length of stay to a maximum of eight times the current utility value.

The four combinations of the descriptive parameters (\( \gamma \) and \( \delta \)) form the basic scenarios for relative comparison. The first scenario, which we will call the "basic" scenario, has the lowest values on all parameters (i.e., \( \gamma = 1 \) and \( \delta = 1 \)) with the length of time that the historical consideration set members have been in the set equal to one period. The second scenario, which we will call the "inertia-dominant" scenario, has identical parameters to scenario one except for the utility adjustments (as a result of inertia as discussed above) where \( \gamma = 4 \) and the assumption that the historical consideration set members have been twice as long in the set (i.e., on the time dimension, we are twice as far into the S-shaped adjustment as in scenario 1). The third scenario, which we will call the "search-cost-dominant" scenario, has identical parameters to scenario one except for the exponential cost decline parameter \( \delta \) which was set equal to 3. Hence, comparing scenario two to scenario one will give insight into the impact of inertia in the sequential evaluation, where comparing scenario three to scenario one will give insight into the impact of rapidly declining decision costs (e.g., as a result of fatigue) in the sequential evaluations. The fourth scenario, which we will call the "combined" scenario, combines the parameter values of scenarios two and three (i.e., \( \delta = 3 \) and \( \gamma = 4 \)). Relative to scenario one, scenario four will give insight into the interaction effect of strong inertia and rapidly declining decision making costs; relative to scenarios two and three, scenario four will give insight into the main effects versus the interaction effects of the manipulated dynamics.

For each scenario, we report consideration set results across 500 replications varying the preference distributions (i.e., the five patterns discussed above), the historical consideration set sizes (one, four, and ten), and the level of confidence (\( \alpha = 0.1, 0.5, \) and 0.9). The universal set of all brands was fixed at ten. The brands belonging to the historical consideration set were picked at random out of this universal set. The discussion of the results focuses on derived set sizes as well as dynamic patterns inferred from relative comparisons across the extreme scenarios.

The mean consideration set sizes together with their variances across the replications are summarized in Table 1. To more fully appreciate the dynamics of the consideration set generation process, Table 2 summarizes the likelihood of expansion and contraction. In the basic scenario, the mean consideration set size ranges from 1 to 7 with the majority of values
| Number of Brands in Consideration Set at 1 | Degree of Confidence (0) | Basic Scenarios | Asymmetric Utility Distributions | Symmetric Utility Distributions | Inertia Dominant Scenario | Asymmetric Utility Distributions | Symmetric Utility Distributions | Search Cost Dominant Scenario | Asymmetric Utility Distributions | Symmetric Utility Distributions | Combined Scenario | Asymmetric Utility Distributions | Symmetric Utility Distributions |
|------------------------------------------|--------------------------|----------------|-------------------------------|-----------------|--------------------------|-------------------------------|-----------------|--------------------------|-------------------------------|-----------------|--------------------------|-----------------|-------------------|--------------------------|
|                                          | (1.03)                   | (2.55)         | (3.01)                        | (1.00)          | (1.45)                    | (0.97)                        | (1.95)          | (1.01)                   | (2.07)                        | (2.71)          | (1.98)                   | (0.45)          | (0.64)            | (1.37)                   | (2.41)          | (4.55)            | (0.68)          | (1.70)            | (1.86)                     | (2.60)          | (2.60)          |
| 0.5                                      | 4.25                      | 6.02           | 6.21                          | 7.11            | 7.02                      | 4.13                          | 5.75            | 5.99                     | 6.21                          | 5.74            | 9.14                     | 9.65            | 9.63              | 9.34                     | 8.73            | 8.27              | 9.61            | 9.23              | 9.03                     | 8.49              | (2.60)          |
|                                          | (1.02)                   | (2.35)         | (1.01)                        | (1.00)          | (1.43)                    | (0.94)                        | (1.69)          | (1.28)                   | (2.33)                        | (3.09)          | (2.67)                   | (0.59)          | (0.92)            | (1.39)                   | (2.39)          | (5.44)            | (0.94)          | (2.10)            | (1.82)                     | (7.67)          | (2.67)          |
| 0.9                                      | 4.22                      | 5.82           | 6.20                          | 7.06            | 6.91                      | 3.93                          | 5.41            | 5.88                     | 5.23                          | 4.88            | 9.56                     | 9.72            | 9.71              | 9.44                     | 8.77            | 7.70              | 9.57            | 9.29              | 8.99                     | 8.40              | (2.67)          |
|                                          | (1.00)                   | (1.73)         | (1.00)                        | (1.00)          | (1.60)                    | (1.03)                        | (1.34)          | (1.41)                   | (3.92)                        | (3.98)          | (1.16)                   | (0.49)          | (0.92)            | (1.19)                   | (2.35)          | (6.56)            | (1.17)          | (2.00)            | (1.93)                     | (2.69)          | (2.69)          |
| 4                                        | 0.1                      | 3.60           | 5.38                          | 5.99            | 5.88                      | 5.27                          | 2.67            | 2.17                     | 2.74                          | 2.25            | 2.05                     | 8.00            | 9.33              | 9.89                     | 9.85              | 9.65              | 6.15              | 5.96              | 7.71                     | 6.81              | 6.16              |
|                                          | (1.11)                   | (1.32)         | (3.00)                        | (5.22)          | (4.97)                    | (0.61)                        | (0.55)          | (1.23)                   | (0.20)                        | (0.53)          | (7.66)                   | (2.85)          | (0.64)            | (0.78)                   | (1.43)          | (9.06)            | (0.69)          | (9.53)            | (11.00)                    | (11.21)         | (11.21)         |
| 0.5                                      | 3.00                      | 4.25           | 4.10                          | 4.62            | 4.47                      | 2.45                          | 1.78            | 2.33                     | 1.93                          | 1.61            | 7.82                     | 9.43            | 9.94              | 9.00                     | 9.57            | 6.07              | 6.31            | 7.20              | 7.18                     | 5.78              | 7.58              |
|                                          | (0.92)                   | (1.98)         | (2.70)                        | (5.66)          | (5.84)                    | (0.64)                        | (0.73)          | (0.83)                   | (0.87)                        | (0.58)          | (8.19)                   | (2.68)          | (0.51)            | (0.46)                   | (1.73)          | (8.22)            | (2.73)          | (10.92)           | (11.13)                    | (9.96)          | (9.96)          |
| 0.9                                      | 2.58                      | 3.44           | 3.92                          | 3.41            | 2.89                      | 2.05                          | 1.75            | 1.35                     | 1.27                          | 1.26            | 6.63                     | 9.13            | 9.56              | 9.29                     | 8.65            | 5.17              | 6.73            | 8.16              | 7.56                     | 5.56              | 7.56              |
|                                          | (0.67)                   | (2.79)         | (4.44)                        | (3.18)          | (1.61)                    | (0.67)                        | (0.74)          | (0.34)                   | (0.27)                        | (0.23)          | (9.99)                   | (2.45)          | (4.30)            | (0.63)                   | (7.42)          | (8.65)            | (4.46)          | (6.71)            | (10.54)                    | (10.54)         | (10.54)         |
|                                          |                           |                |                               |                 |                           |                               |                 |                           |                               |                 |                           |                 |                 |                           |                 |                 |                           |                 |                 |                           |                 |                 |

a Total number of brands equals 10; 500 replications.

b Variance of utility distributions across brands (Beta(p,q)).

c Variance in consideration set sizes.
# Table 2

Likelihood of Expansion and Contraction of Consideration Sets

<table>
<thead>
<tr>
<th>Number of Consideration Sets</th>
<th>Likelihood of Expansion (Expanding)</th>
<th>Likelihood of Contraction (Contraction)</th>
<th>Total Number of Utility Distributions</th>
<th>Variance of Utility Distributions</th>
</tr>
</thead>
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<tr>
<td>10</td>
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<td>0.5</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>5</td>
<td>0.3</td>
<td>0.7</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>0.9</td>
<td>0.1</td>
<td>0.5</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>0.7</td>
<td>0.3</td>
<td>0.7</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
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<td>0.7</td>
<td>0.3</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>0.1</td>
<td>0.9</td>
<td>0.1</td>
<td>1.00</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Note: Total number of brands equates 10; 500 replications.

Variance of utility distributions across brands (Heckathorn).
in the range of 2 to 6. When the historical consideration set is large, the corresponding results in Table 2 indicate that contraction is almost certain. As one would expect, the mean consideration set sizes in the inertia-dominant scenario are smaller than those obtained for the basic scenario, ranging from 1 to 6. In this instance, the contraction of the set is even more pronounced when the historical consideration set is large. In the search-cost-dominant scenario, the corresponding means are larger than the ones obtained for the basic scenario, ranging from 5 to 10. The corresponding results in Table 2 indicate a strong tendency for expansion when historical consideration sets are small. These results are consistent with expectation about the categorization process given high learning rates in decision making costs. In the combined scenario, the mean consideration set sizes are larger than the corresponding values in the basic scenario in most cases but smaller in others. The corresponding dynamic effects in Table 2 are a combination of the previous two scenarios with an apparent dominance of search economies over inertia effects. Further discussion of these dynamics follows.

Despite the extreme character of some simulated instances, the majority of the mean consideration set sizes are well within the range of values reported in the literature. Hauser and Wernerfelt (1990), reviewing the empirical evidence in aided-recall based studies, cite a range of mean values from 2 to 8 with most sizes in the range from 3 to 6. Similar evidence is reported in Reilly and Parkinson (1985) and Urban (1975). Alba et. al (1991) suggest that consideration set sizes are somewhat smaller than the values cited by others when alternatives have to be recalled from memory. Most results in Table 1 are also in the range of the "magic" seven, plus or minus 2 proposed by Miller (1956) as a result of his review of a large number of studies on the human limitations in information processing capacity. In light of these findings, our mean results already provide some face validity for the suggested consideration set generation model. Although possibly influenced by numerical assumptions such as the size of the universal set of brands, the face validity provided by the mean consideration set sizes is enhanced by the expansion and contraction patterns shown in Table 2 which indicate that sizes move generally in the direction of the values reported in the literature.

Stronger face validity can be obtained from relative comparisons which characterize the inherent dynamics of the suggested consideration set generation process and contrast those to behavioral theory and observation. As discussed above, motivation and social context affect decision making (Bettman et. al. 1991). They were considered in the model to underlie and affect the individual's level of confidence in the decision. They are also likely to affect the degree of involvement of the individual decision maker (Shugan, 1980). Social judgment theory suggests that "uninvolved consumers are willing to consider a wider number of brands because of a lack of commitment to one or several brands" (Assael 1981, p.86).
Hence, this theoretical argument would suggest that in our modeling framework, consideration set sizes would decrease with increased levels of confidence sought. The mean consideration set sizes reported in Table 1 are generally consistent with this consumer behavior theory. A few minor deviations from the pattern occur in the search-cost-dominant scenario when the historical sets are moderate to large relative to the size of the universal set.

As discussed above already, large historical consideration sets contract where small historical consideration sets expand. The results in Table 2 indicate that the degree of contraction of large sets is mitigated by search cost economies. When the latter are relatively moderate (i.e., the basic scenarios and the inertia-dominant scenario), contraction is virtually certain. When search cost economies are very large (as in the search-cost-dominant scenario), the likelihood of contraction is much smaller. This pattern is in line with consumer behavior research on knowledge and expertise which suggests that, relative to novices, experts have lower decision costs and evaluate more brands. In memory research, for example, Johnson and Russo (1984) have established that prior knowledge about alternatives is positively related to memory for information about the alternatives in a judgment task. In other words, greater knowledge aids memory. Given the importance of memory recall in the consideration set generation process as discussed above, a knowledgeable individual will have lower information acquisition costs. More importantly, Brucks (1985) has shown that experts search more efficiently and selectively than novices, suggesting more efficient, and hence less costly, information processing. Some consumer behavior research suggests that because of this, experts will evaluate more brands (for a review, see Alba and Hutchinson 1987).

The degree of expansion of small historical consideration sets is mitigated by inertia effects. As one would expect in general, inertia dampens likelihood of expansion in favor of a status quo. It is interesting to note, however, that the magnitude of this expected effect is strongly influenced by the individual's preference distribution across the brands. In contrast to all other utility distributions, the left-skewed pattern shows only a moderate impact of inertia on likelihood of expansion, particularly when confidence is not that high. In other words, when the individual likes few brands and does not look for high levels of confidence, expansion of the consideration set will occur despite inertia in the evaluation process.

This result is one example of numerous context effects which are apparent in the results and which arise from the preference distributions across brands. Another example is that for the symmetric utility distributions, the range of mean consideration set sizes is smaller (and in many cases much smaller) than the difference in mean consideration set sizes between the left-skewed and the right-skewed utility distributions. Despite larger utility variances in the symmetric distributions, this pattern is true across scenarios, levels of confidence, and
historical consideration set sizes. Furthermore, some results are contingent on whether or not the preferred brands were already in the consideration set. As indicated above, brands were randomly assigned to the historical set. Hence, in some of the replications, preferred brands belonged to that set, and in others they did not. In scenarios with very high search cost economies, the frequency distribution of the consideration set sizes over the 500 replications was bimodal, indicating divergence. Although not reported here, further analysis revealed that the divergence was contingent on whether or not the preferred brands were in the historical consideration set. When the brands not belonging to the set had substantially larger deterministic utilities than those belonging to the set, an expansion in set size was generally observed. When the opposite was true, set sizes generally contracted.

The general issue of context effects has received a lot of attention in the behavioral decision theory literature (for a review, see e.g., Bettman et al. 1991). Context effects refer to factors describing a particular set of alternatives. Unfortunately for our work, most of the research has focused on similarity, attribute correlation, and comparable versus noncomparable alternatives. As Bettman et al. (1991) report, there has been little consumer behavior research on the context factor of the overall quality of alternatives. When alternatives are mostly good (i.e., right-skewed utility distribution in our framework) or mostly bad (i.e., left-skewed utility distribution), decision making strategies may be different. Our results here suggest that the judgment task in the categorization process may be equally affected. Because of the paucity in consumer behavior research, we cannot enhance the face validity of the suggested consideration set generation process with the observed context effects. It is, nevertheless, encouraging that the consideration set generation model does recognize the importance of context effects.

In sum, the numerical analysis supports operational robustness as well as face validity. The mean consideration set sizes derived are well within the ranges of observed values. The dynamics of the process further enhance the validity of those results, and a number of patterns were found to be supported by consumer behavior theory. Within the validation limitations of a descriptive model of a latent process, the suggested consideration set generation model does stand up to the test.
CONCLUSION AND DIRECTIONS
FOR FUTURE RESEARCH

The robustness of choice model estimates when the consideration set generation phenomenon is ignored have been drawn into question in the literature. As these estimates have become a basis to evaluate the effectiveness of marketing programs and to derive more efficient and optimal marketing mix decisions, the validity of the latter are undermined by the lack of robustness. To enhance the managerial usefulness of discrete choice models, substantial efforts recently have been devoted to conceptualizing and modeling the consideration set generation process in the marketing literature. This paper developed a rational model of the consideration set formation process at the individual level characterizing that process as a categorization task driven by sequential search balancing incremental benefit with search costs.

The development of the model is grounded in consumer behavior theory recognizing the importance of memory recall in grocery shopping situations, the judgment processing inherent in a categorization task, and the use of simplifying heuristics to limit cognitive effort in the task as well as the decision. The contribution of the model lies in the representation of the search process and the tradeoff heuristic in the utility domain. This is not only consistent with the nature of the task, but provides a convenient way to operationalize a number of consumer behavior phenomena which have been observed in such a task. With the ultimate objective of integrating the model into a choice model to enhance the validity and usefulness of the latter, the utility domain provides a natural link given that most discrete choice models used in practice rely on utility maximization as the rational choice rule. Numerical validation of the latent process model established its numerical robustness as well as face validity in light of published results on consideration set sizes and consumer behavior theory and observation. Given its theoretical grounding and face validity, the proposed model can enhance choice modeling and managerial insights in the choices consumers make.

Consistent with the ultimate objective of consideration set modeling, the next step is to integrate the process model developed here into a choice model. Given the discrete categorization of brands, the outcome of the consideration set generation process can be directly integrated into a discrete choice model such as the multinomial logit. Furthermore, given the operationalization of the process in the utility domain, the consideration set generation model can be estimated iteratively with the choice model. Specifically, initial brand utilities could be derived at each observed choice occasion from the estimates of, for example,
a standard multinomial logit model. These utility values, together with initial parameter values for the consideration set generation process, could be used to derive consideration sets at each choice occasion. With these set definitions, the logit model could be re-estimated and new utility values could be derived. Focusing on the fit of the choice model, this iterative process could be repeated sequentially fine-tuning the parameters of the consideration set generation process. This iterative estimation approach would enable full estimation of the model without any external observation on the process. Hence, besides its theoretical grounding and validation, the consideration set generation model proposed here provides significant operational advantages.

The proposed model also provides some interesting challenges. As the numerical validation results showed, some complex context effects arise in the judgment task inherent in the categorization process. On one hand, the results provide a basis for hypothesis formulation about the behavioral details of this task so far not discussed in the behavioral decision theory literature; on the other hand, the results push for further theoretical conceptualization of the categorization task. These challenges, when confronted successfully, will eventually enhance our understanding of this important process and enhance the explanatory power of the consideration set generation model and, ultimately, the choice model.

The managerial usefulness of the consideration set generation model itself will ultimately depend on the establishment of the determinants of the utility evaluations in the categorization task. Although, as discussed in this work, overlap in determinants is possible in utilities underlying the judgment task and the choice task (such as, e.g., brand preference), it is possible that some marketing mix elements are more effective in influencing the categorization task than the selection task. Such possible differences in effect channel have been suggested in the recent literature (see, e.g., Vanhonacker 1993). More theoretical and conceptual development is needed here. The model suggested and supported in this research provides an operational vehicle to empirically test differential effects. Moreover, in addition to enhancing the robustness of choice model estimates, managerial insights in categorization effects versus selection effects of marketing programs will ultimately establish this model as a operational tool in more effective and efficient marketing decision making.

Despite the encouraging results, certain limitations do characterize the work reported here. First, the consideration set generation process is assumed to be rational. Although in line with various recent conceptualizations, the question still remains as to whether a rational approach provides an adequate representation. Second, the consideration decision is cast in the utility domain using a compensatory model; as suggested in Roberts and Lattin (1991), the
modeling and cross-validation of the conjunctive aspects of the formation process are areas warranting further attention. Third, focus in the numerical analyses was primarily on the general patterns in summary statistics. More work needs to be done on individual brand movements in and out of the consideration set. For example, if our results showed no change in the consideration set size from the historical size, there is still the intriguing question of whether or not the identical brands were retained. This requires further analysis of the utility profiles of brands in the consideration set versus the profiles of those not in the set. Such analyses are further provoked by some bi-modal frequency distributions obtained in this research. Finally, as with any numerical work, it is difficult to argue the completeness of the reported results. An attempt was made to consider many realistic and potentially interesting scenarios.

Research reported in this work makes the notion of consideration set come to life. It is hoped that along with the recognized managerial relevance of the notion, this work stimulates further research.
REFERENCES


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