Glen L. Urban, John S. Hulland, & Bruce D. Weinberg

Premarket Forecasting for New Consumer Durable Goods: Modeling Categorization, Elimination, and Consideration Phenomena

The authors extend previous models for premarket forecasting of new durable consumer goods by including parameters that reflect consumers' categorization and consideration processes. They propose a model and measurement methodology, which they apply to the premarket forecasting of a new automobile. They describe empirical data collection, parameter estimation, managerial implications, validation issues, and future research needs. The extended model generates new managerial insights into positioning and marketing planning effectiveness, can be used to simulate the effects of changes in positioning strategy on consideration and choice, and provides more detailed information about why consumers consider or reject a new brand. The relevance of the categorization extension for other new product models that condition choice on a consideration set is also explored.

MANY consumer product categories can be characterized as "crowded." For example, a potential buyer can choose from more than 300 distinct auto models, more than 30 personal computers, or more than 30 deodorants. However, an individual consumer is unlikely to evaluate all choice alternatives on any given purchase occasion. Customers simplify their decision making by eliminating alternatives from consideration. For example, the median number of cars considered by a U.S. consumer is 8.1 (Hauser, Urban, and Roberts 1983).[1]

Glen L. Urban is Professor of Marketing, Sloan School of Management, Massachusetts Institute of Technology. John S. Hulland is Assistant Professor of Marketing, Western Business School, University of Western Ontario. Bruce D. Weinberg is Assistant Professor of Marketing, School of Management, Boston University. The authors gratefully acknowledge the substantial financial support of a major U.S. automobile manufacturer that enabled us to conduct the research. The second author also acknowledges the financial support of the Social Sciences and Humanities Research Council of Canada for this work. The authors appreciate the design ideas and research support provided by Deborah Marlino, Frank Kardes, Cheena Srinivasan, Jessamy Tang, and John Dabels.

Managers need to understand the nature of these restricted consideration sets, because the marketing strategy for gaining entry into the consideration set may be different from that for maximizing choice once the brand is considered. Managers also need to know the set of competitive brands with which consumers categorize a new product.

Present premarket new product forecasting procedures model how consumers gain awareness of a new brand or are based on the assumption that consumers already employ a particular consideration set of alternatives prior to beginning the analysis. We extend new durable consumer product forecasting models to explicitly include the fundamental behavioral phe-

[1]See Hauser and Wernerfeit (1990, p. 394) for a tabulation of data on consideration set sizes for packaged goods.

nomena of categorization and consideration. This extension enables the model's user to examine how changes in positioning or marketing communication strategy influence consumer consideration for the new brand. Because there are fundamental differences in consumers' perceptions of new products, the proposed disaggregated model affords a richer exploration than present models of the effects of alternative positioning strategies on consumer consideration and choice.

We begin by reviewing relevant behavioral factors that influence the probability of consideration and then incorporate the processes of categorization, elimination of categories, and consideration into a specific aggregate customer new product forecasting model. We propose a measurement and estimation methodology and provide an illustrative application in the automobile market. Finally, we discuss future research needs and potential extensions of our approach to various new product forecasting models in which choice is conditioned on a consideration set.

Consideration and Categorization

Behavioral Foundations

A growing body of experimental research suggests that individuals use phased decision heuristics when faced with complex, multi-alternative decision environments (e.g., Lussier and Olshavsky 1979; Payne 1976; Payne, Bettman, and Johnson 1988). The first phase of such a strategy involves the use of a noncompensatory decision rule to eliminate most alternatives in a product category from further consideration. Subsequent phases involve more detailed, compensatory evaluations of the surviving alternatives if more than one alternative survives the first phase.

These findings are consistent with a framework originally developed by Howard and Sheth (1969). They suggested that consumers might use a simple information processing heuristic to screen a large initial set of alternatives down to a much smaller set of relevant brands. Howard and Sheth referred to this smaller set of brands as the "evoked set," and argued that an individual consumer's product choices are made exclusively from this reduced set. Though the exact composition of the relevant set may be difficult to define (e.g., see Alba and Chattopadhyay 1985, Parkinson and Reilly 1979, and Silk and Urban 1978 for alternate definitions), the construct has proven to be useful in marketing. Considerable theoretical and empirical work of the past two decades has examined the size of consumers' consideration sets (see Roberts and Lattin 1991, Hauser and Wernerfelt 1990, and Roberts 1989 for reviews).

Many consumer heuristics involve the organization of product knowledge in memory into categories. Consumers use product categories to structure product knowledge in a meaningful, simplified manner, which helps them to make ongoing evaluations. For example, if a new product is categorized as belonging with other, attractive alternatives (e.g., members of the consideration set), it is more likely to receive further attention than if categorized with a set of unattractive products (e.g., Sujan 1985; Sujan and Bettman 1989).

An important issue in using consumer categories to assess the potential success of a new product is whether those categories apply in all situations. In some choice contexts, the categories used by consumers are not predetermined, but instead depend on the consumers' goals during specific choice occasions (e.g., Barsalou 1985; Park and Smith 1989). Intended usage has often been used as a proxy for consumers' choice goals and has been helpful in clarifying market structure (Srivastava, Leone, and Shocker 1981; Urban, Johnson, and Hauser 1984), as has substitution in use (Ratneshwar and Shocker 1991). However, these approaches are likely to be more important in broadly defined categories such as snack foods or automobiles than in narrowly defined categories such as cream-filled cookies or subcompact cars.

In the market structure analysis we use, individual consumers are assumed to have already eliminated many categories of product alternatives from further consideration. This approach is consistent with an initial broad partitioning of the market into aggregate categories (based on usage goals or substitution in use, for example) followed by a more intensive evaluation of alternatives that fit within a few specific categories.

Incorporating categorization principles in a new product model has the potential to generate new insights and lead to more effective marketing strategies, particularly when the new product differs significantly from current products. In such cases, a manufacturer can position the new product as either similar to or distinct from current offerings (e.g., Sujan and Bettman 1989). These alternative category positionings have very different implications for consumer consideration and choice of the new product.

Aggregate Forecasting Models

The modeling work by Bass (1969), Urban (1970), and Massy, Montgomery, and Morrison (1970) provides three well-known examples of aggregate forecasting models in which consumers are assumed either to be already aware or to quickly become aware of a new product. None of these three models incorporate individual differences in consumers' consideration sets.

Conjoint choice models, in which a fixed set of relevant attributes is assumed, require individual-level utility measurements on an attribute-by-attribute basis. More advanced versions have been used to determine market share through discrete choice analysis (e.g., Green and Srinivasan 1978). Though it is possible theoretically to use utility-based choice models based on individuals' self-identified consideration sets, researchers have commonly preferred to define the relevant set prior to utility measurement on the basis of hypothetical profiles or attributes that are assumed to be considered by consumers.

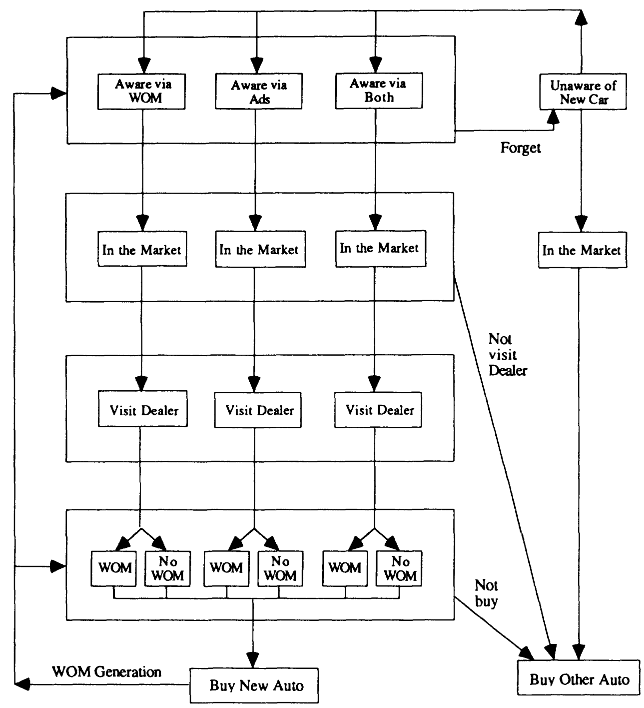
Aggregate choice models that in part address consideration sets have been developed (e.g., Guadagni and Little 1983; Roberts and Urban 1988; Silk and Urban 1978). They include an explicit set based on new product forecasts or estimate logit parameters over the consideration set. However, they do not model customers' categorization of acceptable and unacceptable brands. Recently, Ben-Akiva and Boccara (1990) have proposed a model that builds on previous efforts to define hierarchical probabilistic choice models (e.g., Gensch 1987; McFadden 1980). They model choice as a two-step process of probabilistically selecting a choice set from all possible subsets of alternatives and then choosing a brand from the choice set.

Our objective is to extend aggregate new product forecasting models to include the important behavioral phenomena of categorization and consideration. We describe our modeling extension in the context of a specific durable goods new product forecasting model developed by Urban, Hauser, and Roberts (1990). We develop a model, measurement, and estimation methodology and then apply it empirically in the context of a new car launch.

Model Structure

The new auto forecasting model developed by Urban, Hauser, and Roberts (1990) is based on the durable goods model of Roberts and Urban (1988) and is shown in Figure 1 in its "macro-flow" format. Customers are defined as being in decision process states, and they flow from one state to another as a result of their search for information and marketers' actions. Customers move from being unaware to being aware of advertising for the new model at some rate per month dependent on advertising expenditures. For example, suppose 10 million customers are initially unaware of a new product and 10% gain awareness in the first month after its launch through advertising. Then 1 million will be placed in the "aware via ads" box in Figure 1. If 5% of these individuals are in the market for a car that month, 50,000 people will flow to the "in the market" box. Furthermore, if 30% of these people visit one or more dealers carrying the new product, 15,000 will flow to the "visit dealer" box. Customers not visiting the new car dealer are assumed to visit other dealers and buy an alternate car, because they are currently "in the market" and assumed ready

FIGURE 1
Behavioral States Macro-Flow Model for a New Automobile[a]



[a]Adapted from Urban, Hauser, and Roberts (1990).

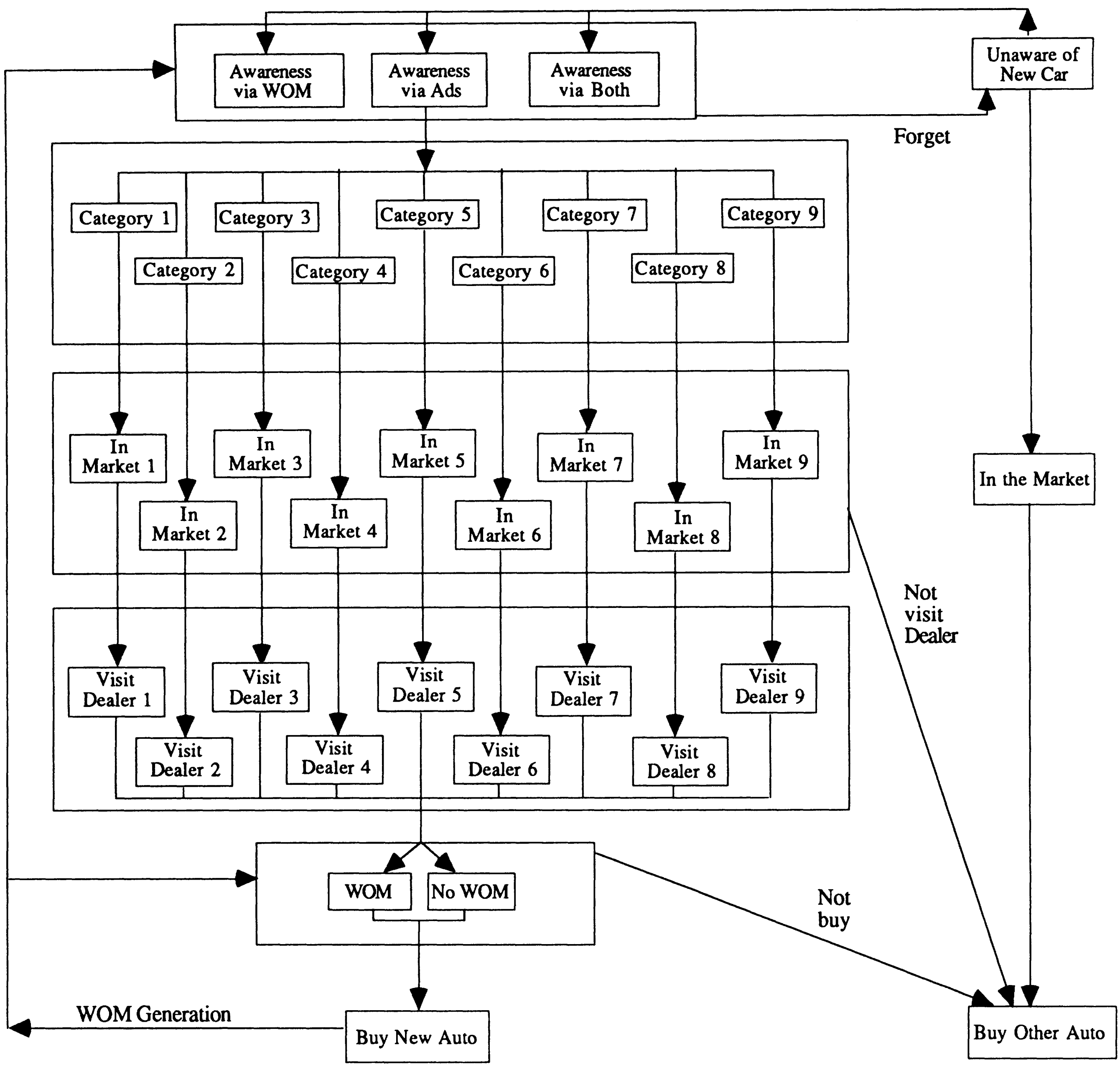
to buy. Finally, if 75% of customers visiting a dealer do not receive word-of-mouth communication from other customers and one third of them buy the car, and if one-half of the remaining 25% who do receive word-of-mouth recommendation buy the car, the first month sales forecast would be 5625 units (15,000 × .75 × .33 + 15,000 × .25 × .5). Other flows are defined to describe loss of awareness ("forgetting") and the generation of awareness via word-of-mouth communication.

Flow parameter estimates are based on results from a prelaunch market research clinic.[2] Though this model encompasses many customer information and decision steps, it does not include the key behavioral factors of consideration through categorization and elimination of alternatives.

Extending the model to include consideration is conceptually simple. New states representing separate categories of brand alternatives and parameters defining the fraction of brands considered in each category are added. Figure 2 shows the extended flow model for the "awareness via ads" state for an arbitrary set of nine categories. In each application, the number of

[2]Urban, Hauser, and Roberts (1990) provide a complete description of this model structure and its estimation and validation. A general discussion of their approach is provided in Appendix A.

FIGURE 2
Expanded Macro-Flow Model Incorporating Categorization for Advertising Awareness Cell



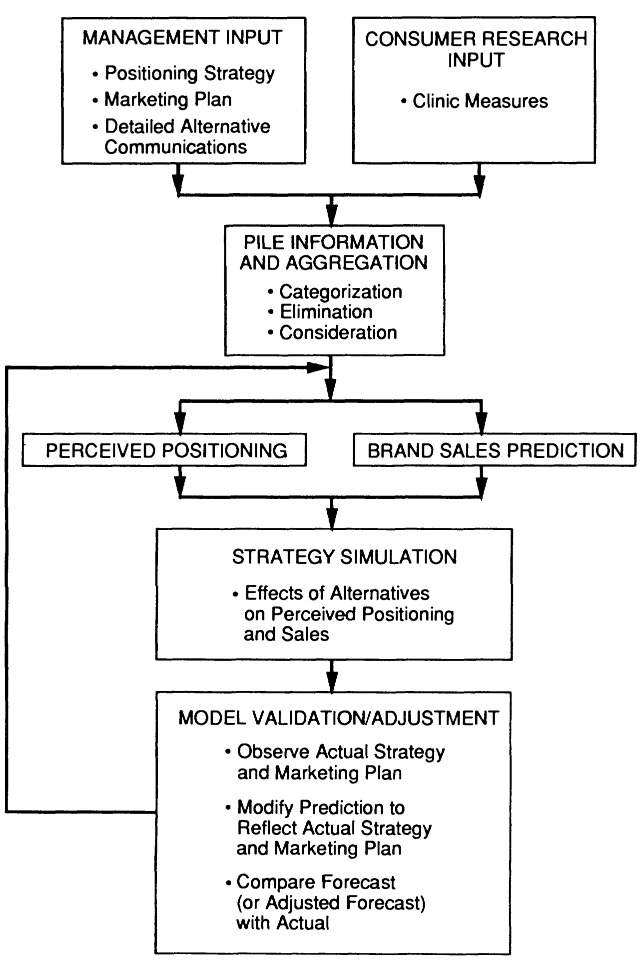
categories and their brand compositions must be determined empirically (see the following section for a more detailed discussion of this issue). Similar categorization breakouts are modeled for the "aware via word of mouth" and "aware via both ads and word of mouth" states, but are not shown in Figure 2. Each consumer included in the model estimation process is assigned to one category. The model then keeps track of the proportion of individuals in a category who are in the market at the present time and the proportion who visit a dealership to see the new product. As a result, there is a one-to-one correspondence between the category, in the market, and dealer visit states, as shown in Figure 2.

The fraction of consumers who are in the market for the overall product class can vary by category. Consideration for the new brand will depend on the categorization state whenever some categories are eliminated or become less desirable than others. The new brand consideration proportion is likely to be high in favorable categories, where all or most of the choice alternatives in the category are considered, and low in categories that contain many eliminated alternatives. Once a dealer visit has been made for the new durable good, we model the post-visit word-of-mouth effects and buying probabilities as in Figure 1.

Measurement and Estimation

Though the extension to the model structure is straightforward, the increase in the number of states and flows is large and the measurement, aggregation, and estimation procedures for the extended model are not obvious. An overview of the general measurement procedure for the extended model is provided in Figure 3. The management and consumer research input stages for the extended model are very similar to those in the base model of Figure 1 (see Appendix A). However, the next stage in Figure 3, pile information and aggregation, is unique to the extended model. Individual-level measures of perceived similarity and consideration are used to estimate aggregate categorization, elimination, and consideration phenomena. This information is then used to determine the new product's perceived positioning and to develop a sales forecast. By incorporating consumers' responses in the clinic setting to alternate positioning strategies (as translated into actual marketing communications), the extended model can be used to simulate the effects of these alternate strategies on consumers' brand perceptions and expected sales volume. Finally, the model should be validated by comparing its sales forecasts with actual sales. If the implemented marketing plan deviates significantly from the original plan, the model's forecasts should be revised on the basis of the realized marketing program.

FIGURE 3
Modeling and Measurement Procedure



To measure individual categorization, one must first decide whether the overall category definition is to be narrow or wide. For example, modeling all vehicles that cost between $10,000 and $20,000 is much more complex than forecasting a new entrant in the category of two-seat sports cars priced at more than $20,000. In most new product premarket forecasting applications, the target market has been identified very precisely, the usage scenario specified, and the core benefit proposition defined. In such cases, a narrow overall product category definition is appropriate. We assume here that the product and the marketing strategy are designed for a well-defined category, and then model the subcategories as shown in Figure 2.[3]

To begin the categorization measurement, each respondent receives a deck of cards representing the entire set of currently available alternatives in the product category. Each card represents one choice alternative, with a photograph on the front and a short list of product attributes on the back. The respondent identifies the subset of products with which he or she is familiar, without referring to the attribute information on the reverse of each card. The unfamiliar choice alternative cards are then removed from the deck, and the respondent sorts the remaining cards into piles so that each pile contains "similar" alternatives. Finally, the respondent identifies the consideration set.

Categorization, Elimination, and Consideration Probabilities

Each pile formed in the sorting task represents a separate subcategory within the overall product category. A consumer's categorization process is measured by the number of piles formed and by the composition

[3]When a wide category is defined, usage scenarios would have to be considered. In structuring the market for cars in the price range of $10,000 to $20,000, the use of the car in commuting, vacations, or family suburban trips may be the basis of categorization. This could require measurement of similarity and preference by use, or appropriateness measures by use (e.g. Srivastava, Leone, and Shocker 1981), and statistical testing of usage-based categorization versus other bases of segmentation (see Urban, Johnson, and Hauser 1984).

of those piles. Typically, these measures are heterogeneous across individuals.

To define the elimination process for an individual, we examine the extent to which the consideration set is represented in the various piles. At one extreme, an individual might place all consideration set alternatives in a single pile. At the other extreme, the consideration set elements could be spread out over all piles formed. This span of the consideration set across piles represents the extent to which an individual employs a categorization-based strategy of elimination. An individual with a consideration set across many piles is willing to consider (at least tentatively) many subcategories of alternatives, whereas an individual with a concentrated set eliminates most of these subcategories from active consideration.

Product consideration depends on both the categorization and elimination processes. A new product will have the potential to be considered only if it is categorized as belonging to a set of alternatives that have not been eliminated previously during a consumer's decision process. Even then, however, the new brand may not subsequently be considered seriously for purchase, because all items in a category are not necessarily considered. (A hypothetical example of one individual's pile formation, categorization, elimination, and consideration processes is provided in Appendix B.)

These processes can be described in a more formal probabilistic manner. Define n_f to be the number of alternatives with which the respondent is familiar, n_c to be the number of alternatives in the individual's consideration set, n_e to be the number of alternatives eliminated from consideration by being placed in piles that contain no members of the individual's consideration set, and n_e' to be the number of alternatives eliminated from piles containing at least one considered alternative (see Appendix B for an example). Note that $n_f = n_e + n_e' + n_c$. In addition, define P(E) as the probability that an average alternative is eliminated by categorization, $P(\bar{E})$ as the probability that it is not eliminated by categorization, P(C) as the probability that it is considered, and $P(C|\bar{E})$ as the conditional probability that it is considered given that it is not eliminated initially by categorization. Then:

$$P(E) = n_e/n_f \tag{1}$$

$$P(\bar{E}) = 1 - P(E) = (n_f - n_e)/n_f \tag{2}$$

$$P(C|\bar{E}) = n_c/(n_f - n_e) = n_c/(n_e' + n_c) \tag{3}$$

$$P(C) = (n_c/n_f) = P(C|\bar{E})P(\bar{E}) \tag{4}$$

Traditionally, P(C) has been employed in aggregate flow models whenever individual consideration sets have been incorporated into the analysis. However, equation 4 is formed from the product of equations 2 and 3. Breaking the probability of consideration into two components allows a deeper examination of the reasons underlying consumer consideration (or rejection). In particular, if consumers tend to view a new brand as belonging to an unattractive category, a new communications strategy can be used to change consumers' perceptions of the new brand and lead them to categorize it as a member of a more attractive category. This change in strategy would be particularly effective if the new brand has desirable features that are likely to lead to a high level of consideration, given only that the brand is no longer dismissed outright.

The preceding results apply to an average item placed randomly in an average pile formed by the individual, but examining the elimination and consideration processes on a pile-by-pile basis is also useful. Define the superscript j to represent the individual categories (or piles) formed in the sort task. Then the total consideration probability for the new brand is:

$$P(C) = \sum_{j=1}^{J} P(C|\bar{E})^j P(\bar{E})^j P(j), \tag{5}$$

where the expressions from equations 2 and 3 are now determined separately for each category formed and where P(j) represents the probability that the new brand will be placed in category j.

Consideration probabilities given by equations 4 and 5 will always be the same. However, the models represented in each case are very different. In equation 4, the new brand is assumed to be typical of products in its subcategory. In equation 5, the model acknowledges that the categorization process may be influenced by a variety of perceptual factors, and that the category chosen for the new brand may vary across individuals; however, once the new brand has been categorized, it is assumed to be perceived as typical of the alternatives in that particular category.

Aggregation Issues

Because the new product flow model forecasting is done at an aggregate level, aggregate categories must be defined to reflect the piles formed by individuals, and average flow proportions must be calculated for each category. These average flow proportions are estimated by assigning each individual to only one of the aggregate categories on the basis of where he or she places the card for the new brand, and then averaging the individual probabilities of considering the car and visiting a dealer.

It is easiest to think of categories defined at the aggregate level as clusters of choice alternatives. Each choice alternative is uniquely assigned to one of these clusters. The composition of these clusters is based on the information from respondents' card piles. Because individuals formed distinct piles of "similar" choice alternatives, this pile information is used to form an N × N symmetric similarity matrix, where N is the total number of alternatives in the product class. For an individual respondent, a matrix element ($S_{i,t}$) equals one if item i and item t were sorted into the same pile and zero otherwise. If an item i is unfamiliar, all rows and columns associated with i in the matrix will equal zero.

An aggregate similarity matrix is then formed by summing these elements across individuals, with the off-diagonal matrix elements representing the number of individuals placing the two items together and the diagonal elements representing the number of individuals familiar with each alternative. Both the number of aggregate clusters and their compositions are based on a hierarchical cluster analysis of this matrix. The reasonability of the cluster solution obtained by this approach is then tested by using a scree test or by examining pseudo F-statistics. Alternatively, the obtained cluster solution can be compared with other possible structures determined on an *a priori* basis by using the statistical testing procedure proposed by Urban, Johnson, and Hauser (1984). Their procedure is based on forced-switching data and generates a normally distributed Z-statistic that is used to test the existence of a categorization structure versus a null hypothesis of no structure.

Assignment of the new brand to one of these aggregate clusters is complex, because each individual may sort the card for the new brand into any of his or her existing piles. The new brand is assigned to an aggregate cluster on the basis of the extent to which it is associated with other alternatives. At the individual level, this procedure leads to the following assignment rule. If the new item is placed with more members of a particular aggregate cluster than with the members of any other single aggregate cluster, the new item is assigned to that cluster for that individual (see Appendix B for an example). When the new item is placed with equal numbers of members from two (or more) clusters, the item is randomly assigned to one of those clusters. An estimated probability (P(j)) that the new product belongs to aggregate category (j) is the result of this process.

Flow model parameters for the proportion of consumers who consider the car and who visit a dealer given that they categorize the new car in a class (j) are then estimated by averaging the probability of visiting a dealer across individuals assigned to category (j).

Application

The preceding prelaunch forecasting model and measurement methodology were applied to the Visala, a two-seat luxury/sports car priced at more than $20,000,[4] 18 months prior to its introduction. Managers were interested in a final sales forecast and marketing recommendations, so that the positioning chosen for the national launch would maximize sales.

Measurement

Individual measures were collected in a clinic that was run over a three-week period during the spring of 1987 in Cincinnati, Ohio. Participants were individuals who were considering a new car purchase within the next three years, were willing to consider purchasing a two-seat car, and were willing to spend more than $20,000 for a new automobile. Individuals participated in the clinic at their convenience and received $50 as compensation for their time. An average clinic session lasted about two hours.

When participants arrived at the clinic, they first received a deck of 69 cards representing models of automobiles available domestically within the sporty two- or four-seat market segment, and then identified the subset of cards with which they were familiar. The familiarity set (n_f) ranged in size from a minimum of 10 to a maximum of 69 cars, and had an average size of 56 cars. Individuals sorted these familiar alternatives into a self-determined number of separate piles. Clinic participants formed an average of eight piles, and the number of piles ranged from a low of two to a high of 27.

Next, participants identified the "most typical" car in each pile, the members of their consideration sets, and their top three choices for a new automobile purchase. The average size of the consideration set (n_c) was seven cars, and size ranged from a minimum of one car to a maximum of 27. Therefore, the average proportion of consideration for this group across all familiar cars was 12.5% ($P(C) = 7/56 = .125$).

Respondents then viewed a concept board (including a picture of the Visala positioned as a "new kind of sports car," combining sporty styling with more comfort and ease of handling). Respondents were given a card with the picture of the Visala on it and asked to put it into a pile with "similar" cars. They then received additional information about the car through a showroom visit, a test drive of a preproduction prototype, and viewing videotapes designed to simulate word-of-mouth communications. Probabilities of purchase were measured after each information exposure, and respondents categorized the Visala after driving it as well as after concept exposure.[5]

[4]The name of the car is coded to protect the proprietary interests of the U.S.A. manufacturer.

[5]See Urban, Hauser, and Roberts (1990) for details of probability estimation. We emphasize only the new categorization results.

Individual Pile Formation Results

The average clinic participant's consideration set spanned five of the eight piles formed, leaving three piles that were eliminated outright from further consideration. In fact, an average participant eliminated 46% of his or her familiar alternatives by placing them in piles that contained no members of the consideration set (see equation 1, $P(E) = .46$, and equation 2, $P(\bar{E}) = .54$). For remaining piles that included at least one member of the consideration set, the average probability of consideration for a car was only 23% (see equation 3, $P(C|\bar{E}) = .23$).

Aggregate Categorization and Consideration Results

The composition of the piles formed by the 434 clinic participants in the sorting task was used to form a 69 by 69 symmetric similarity matrix, which was converted into a dissimilarity matrix and then input to a hierarchical clustering algorithm. Three alternate solutions were obtained, representing five, nine, and 32 clusters or categories of automobiles. The five- and nine-category solutions yielded similar pseudo F-statistics. However, the nine-category solution had greater face validity for senior automotive managers as determined by the relative interpretability of the sets generated in each case. The 32-category solution was less significant statistically and was difficult to interpret. The composition of the nine-category solution is shown in Table 1. In the five-cluster solution, categories 1 through 4 were combined, as were categories 5 and 6. The nine-category solution was selected as the best estimate of the aggregate categories. The Urban, Johnson, and Hauser (1984) procedure described previously was used to test this solution statistically against a hypothesis of no categorization—all cars compete with each other in one group. The overall Z-statistic was 7.1, significant at the .01 level. All Z-statistics for the categories were significant at least at the .05 level and are reported in Table 1. This evidence suggests that, in the aggregate, consumers perceived nine distinct categories for the 69 cars included in the study.

The information contained in the piles of individual clinic participants was reexamined by using the aggregate groups of cars identified in Table 1. Table 2 reports this information by category, aggregated across all individuals. (Note that the calculations were made prior to examining the location of the Visala card for each individual.) For example, the cards representing cars in category 1 (refer to Table 1) showed up in individuals' piles a total of 2015 times. Just over one half of these cards (1061) were in piles that contained no members of individuals' consideration sets (i.e., they were eliminated from further consideration by categorization), leaving 954 of these cards in noneliminated piles. Therefore, the probability of elimination, $P(E)^1$, is .527 (1061/2015). Furthermore, of the 954 category 1 cars placed in consideration piles, only 235 were considered seriously for purchase. Therefore, the probability of consideration for a category 1 automobile given nonelimination, $P(C|\bar{E})^1$, is .246 (235/954).

TABLE 1
Nine-Category Solution[a]

Category 1 (2.6)
Acura Integra
Mazda 626
VW Jetta
Acura Legend
Peugeot 505
Sterling
Audi 4000

Category 2 (2.0)
Alfa Romeo GTV
Maserati Biturbo
Merkur XR4TI
VW Cabriolet
Cadillac Allante
Mercedes 560SL

Category 3 (1.7)
Buick Skyhawk
Pontiac Sunbird
Pontiac Grand Am
Chrysler LeBaron convertible

Category 4 (2.9)
Honda CRX
VW Scirocco
Honda Prelude
Nissan 200 SX
Toyota Celica

Category 5 (3.0)
Chevrolet Camaro
Pontiac Firebird
Pontiac Fiero
Toyota MR2
Mazda RX7
Toyota Supra
Nissan 300ZX

Category 6 (2.4)
Chevrolet Corvette
Porsche 924S
Porsche 944
Porsche 928S

Category 7 (3.1)
Audi 5000
BMW 300
BMW 500
Saab 9000
Volvo 740 GLE
Volvo 760 GLE
BMW 600
Jaguar XJ-6
Mercedes 190E
Mercedes 300E
Mercedes 380

Category 8 (3.8)
Buick Electra
Buick Riviera
Olds 98
Olds Toronado
Cadillac DeVille
Cadillac Seville
Lincoln Town Car
Cadillac Eldorado
Lincoln Mark VII

Category 9 (4.1)
Buick Century
Chrysler LeBaron
Buick LeSabre
Olds 88
Chevrolet Celebrity
Dodge 600
Pontiac 6000
Ford Taurus
Mercury Sable
Buick Somerset Regal
Olds Calais
Olds Ciera
Chevrolet Monte Carlo
Olds Cutlass Supreme
Ford Thunderbird
Mercury Cougar

[a]Figures in parentheses are Z-statistics (see text for details). Z is 1.65 for 5% significance and 2.33 for 1% significance.

TABLE 2
Consideration Probabilities by Category

Category (j)	Total No. of Cards	No. of Cards Eliminated by Catigorization	$P(E)^j$	No. of Cards Remaining	$P(\bar{E})^j$	No. of Cards Considered	$P(C)^j$	$P(C\|\bar{E})^j$
1	2015	1061	.527	954	.473	235	.117	.246
2	1539	695	.452	844	.548	206	.134	.244
3	1509	937	.621	572	.374	128	.085	.224
4	1822	1024	.562	798	.438	179	.098	.224
5	2616	1162	.445	1454	.555	405	.155	.279
6	1460	503	.344	957	.656	314	.215	.328
7	3592	1295	.360	2297	.640	638	.178	.278
8	3510	1537	.438	1973	.562	473	.135	.240
9	6030	3575	.593	2455	.407	373	.062	.152

$P(E)^j$ = probability of elimination of car in category j = number of cards eliminated/number of total cards
$P(\bar{E})^j$ = probability of car *not* being eliminated in category j = 1 − $P(E)^j$ = number of cards remaining/number of total cards
$P(C)^j$ = probability of consideration of car in category j = number of cards considered in category j/number of total cards
$P(C|\bar{E})^j$ = probability of consideration of car in category j given that car is not eliminated = number of cards considered/number of cards remaining = $P(C)^j/P(\bar{E})^j$

This method of calculating a conditional consideration probability was repeated for all nine categories. The probability of initial elimination, $P(E)^j$, ranges from a low of .344 (category 6) to a high of .621 (category 3). Therefore, individuals are most likely to screen out category 3 automobiles, and are particularly likely to consider further category 6 automobiles. The values of $P(C|\bar{E})^j$ range from .152 (category 9) to .328 (category 6). That is, among automobiles that are not eliminated outright, category 9 cars are relatively less attractive and category 6 cars are relatively more attractive. The overall consideration, $P(C)^j = P(C|\bar{E})^j\, P(\bar{E})^j$), ranges from a low of .062 to .215. Clearly, where consumers categorize a new car will significantly affect its sales.

Visala Response

For each individual, the Visala was assigned to one of the nine previously identified aggregate categories by using the assignment rule based on an agreement between the individual and aggregate categories (see previous description and Appendix B). The number of people perceiving the Visala to belong to each of the nine aggregate categories is given in the second column of Table 3 and in probability form in the third column. Many people (43.5%) perceived the Visala as similar to group 5 cars after concept exposure. The overall probability of consideration, $P(C)^j$, for each category is taken from Table 2, and is then multiplied by the probability that the Visala is identified with that category, P(j). The resulting probabilities, $P(C)^j_r$, are the weighted consideration probabilities, by category. Summing these probabilities yields a total probability of consideration for the Visala of 14.7%.[6]

Table 3 also shows the average probabilities of visit for individuals who were assigned to each aggregate category and who would consider the Visala. These values range from .23 (category 8) to .63 (category 3). They suggest that categorization affects the probability of an individual searching for more information about the new car, as well as influencing the elimination and consideration processes.

The net effect of categorization, consideration, and visit phenomena is shown in the probability of consideration and visit, $P(C,V)^j_r$, for the Visala ($P(C,V)^j_r = P(C)^j_r P(V|C)^j_r$). The value ranges from .001 in category 1 to .034 in category 5. Assuming that the final buying decision is conditioned only by dealer visit and word-of-mouth communication after visit (as we do in our model in Figure 2), the probabilities in Table 3 imply that almost one half of all Visala sales will come from people who categorize the car as belonging in group 5 (see the last column, Table 3) and three quarters of Visala sales will come from people who categorize the car in groups 5 and 6.

Model Forecasting and Simulation

The aggregate new product forecasting moael in Figure 2 is used to forecast the base case sales and to simulate the implications of alternate positioning strategies by applying the categorization and visit numbers in Tables 2 and 3 and other inputs to the flow model as described by Urban, Hauser, and Roberts (1990). The four-year base case sales forecast is 71,500 units (see base case row in Table 4).

The base case sales forecast obtained from the extended model (Figure 2) is the same as the forecast

[6]This proportion agrees reasonably well with the average of individual self-assessed probabilities of purchase for the Visala after concept exposure (18.3%), and suggests that the aggregation model is acceptable given that probability of purchase is an adequate surrogate for consideration at the concept exposure level of awareness.

TABLE 3
Determining Visala Consideration and Dealer Visit

Category (j)	n(j)	P(j)	$P(C)^j$	$P(C)_r^j$	$P(V\|C)_r^j$	$P(C,V)_r^j$	Proportion of Total $P(C,V)_r$ (%)
1	4	.014	.117	.002	.50	.001	1.7
2	10	.035	.134	.005	.62	.003	4.3
3	8	.028	.085	.002	.63	.001	1.4
4	15	.052	.098	.005	.29	.001	1.4
5	126	.435	.155	.067	.50	.034	49.3
6	47	.162	.215	.035	.53	.019	27.5
7	20	.069	.178	.012	.51	.006	8.6
8	23	.079	.135	.011	.23	.002	2.9
9	37	.128	.062	.008	.27	.002	2.9
Totals	290[a]	1.00		.147		.069	100.0

[a]The number of observations used in this table is 290 rather than 434. Though there were 434 clinic participants in total, only 290 were directly involved with the Visala. The remaining individuals examined comparable, already available models in order to provide control measures for the Visala forecasts.

n(j) = number of participants placing the Visala primarily with category j cars
$P(C)_r^j$ = weighted consideration probability for category j
$P(V|C)_r^j$ = weighted probability of dealer visit, given consideration, for category j
$P(C,V)_r^j$ = weighted joint probility of consideration and visit, for category j

TABLE 4
Simulated Sales Forecasts for Alternate Positioning Strategies

Positioning Strategy	Sales Forecasts (000's units) Year 1	Year 2	Year 3	Year 4	Total
Base case: new kind of sports car	11.0	16.3	20.3	24.0	71.5
Typical American car	6.6	8.8	10.3	12.0	37.7
Sporty luxury car	6.1	8.0	9.2	10.7	34.0
Performance sports car	12.4	18.8	23.7	27.9	82.9

that would be obtained from the simpler model shown in Figure 1. The advantage of using the extended model is its ability to simulate the effects of alternative positioning strategies on sales. As noted previously, categories 5 and 6 account for most of the forecast sales under the base case positioning strategy (i.e., "new kind of sports car" with comfort and driveability). In contrast, positioning the Visala as a personal luxury car rather than as a sports car could lead to its categorization with cars such as the Buick Electra, Cadillac DeVille, Chrysler LeBaron, Ford Thunderbird, and Pontiac Grand Am (found in categories 3, 8, and 9). This positioning as a luxurious, smaller, personal-sized, but typically American car is simulated by changing the fraction of customers who categorize the car into each category (P(j)). For this simulation, the probabilities of placing the Visala in each category were set to the relative proportion of American cars in categories 3, 8, and 9: $P(j = 3) = .14$, $P(8) = .31$, $P(9) = .55$, and $P(j) = 0$ for the others. Sales decreased dramatically, from 71,500 to 37,700 units over four years (see typical American row in Table 4). Clearly, this positioning strategy is less attractive than the base case alternative.

Another strategy might be to position the Visala as a luxury car, but identify it with the sporty luxury cars in category 8 (e.g., Riviera, Toronado, Eldorado) rather than with the lower priced luxury cars in categories 3 and 9. This positioning strategy was simulated by increasing the category 8 probability to .92 and setting the other eight category probabilities to .01. The forecast sales volume resulting from this simulation was 34,000 units (sporty luxury row in Table 4), which is a little lower than the sales forecast for the typical American car positioning strategy. Though the Visala and the sporty luxury cars of category 8 were similar in power, suspension, and amenities, the different body and interior two-seat arrangement of the Visala led many consumers to assign it to category 5 in the base case. The results from these simulations suggest that using advertising to position the Visala in comparison with the sporty luxury cars is not likely to be successful.

The preceding simulations indicate that a strategy encouraging categorization of the Visala as a new kind of sports car could be successful. To simulate the upside potential of an even more sporty positioning, we changed the probabilities of categorization as follows:

$P(j = 1) = P(2) = .025$, $P(3) = P(8) = P(9) = 0$, $P(4) = .075$, $P(5) = .425$, $P(6) = .350$, and $P(7) = .100$.[7] These probabilities increase categorization of the Visala with cars made by Porsche, BMW, and Mercedes (categories 6 and 7). Forecast sales increased to 82,900 units over four years (performance sports car row in table 4). The results of these simulations suggest that the Visala should be positioned as a performance sports car to achieve the highest sales potential. The assumption, of course, is that the car can fulfill customers' performance expectations.

Additional Managerial Implications

Breaking apart the elimination and consideration steps of the decision process suggests that managers have two problems. First, the car must be positioned so that consumers do not eliminate it outright through categorization. Second, it must have attributes that lead to its being considered and preferred, given that it is not eliminated by categorization. In the Visala case, 45.5% of the clinic participants eliminated the Visala by categorization (calculated by multiplying $P(E)^j$ from Table 2 and $P(j)$ from Table 3, and summing over (j)), and two thirds of those who did not eliminate the car would not consider it. These numbers are significant for a sample of consumers that included only people who were willing both to consider a two-seat car and to spend more than $20,000. Presumably, the elimination was not because of size or price. Advertising to help individuals classify the car in category 6 (e.g., Porsche 944) or 7 (e.g., BMW 300 series) would address the first problem by reducing elimination through categorization.

If a product is categorized correctly, the second problem is positioning within the desired category so that the car is both considered and preferred to other alternatives. Consideration given no elimination through categorization is highest in categories 5, 6, and 7. However, the categorization probability is lower for category 7, so its overall consideration probability $(P(C)^J_r)$ is lower than that of categories 5 and 6. Therefore, targeting categories 5 and 6 should lead to the highest consideration of the Visala. It would be advantageous to have an ad that leads to both correct categorization and within-category positioning, but such an ad may be difficult to devise. A more realistic approach could involve an early campaign to establish categorization, followed by later ads that establish the car's within-category positioning.

Given consideration, perceptual maps for each category can be drawn and used to maximize preference within a category through careful positioning against salient or important attributes. In our case, clinic participants rated all of their consideration set alternatives on 26 attributes. These attributes were factor analyzed, forming three dimensions: (1) sportiness, (2) luxuriousness, and (3) reliability. (The heavy-loading attributes for the factors were (1) fun to drive, sporty, and exciting, (2) luxurious, safe, and comfortable, and (3) reliable, good value for the money, and economical, with eigenvalues of 12.2, 3.7, and 1.8, respectively). We then developed perceptual maps for each category. The Visala was viewed initially as a little less sporty, more luxurious, and less reliable than the typical category 5 (Nissan 300ZX) and category 6 (Porsche 944) cars. Consequently, an ad campaign that positions the Visala as a sporty car and emphasizes its quality and convertible styling could improve consumer acceptance of the new car in these categories. This communication strategy warrants attention because of the large number of individuals identifying the Visala with these two categories and the fact that it reinforces the overall categorization.

Positioning for categorization, consideration, and choice will not be effective if a product does not fulfill its claims. We obtained categorization and rating data after the car was driven as well as after concept exposure. The distributions of where people categorized the Visala after concept exposure and after driving were not significantly different. However, the perceptual ratings on the acceleration, handling, comfort, and roomy interior attributes increased significantly after driving (at the 10% level). Word-of-mouth communication by buyers can be expected to be positive, because the car fulfills or exceeds initial expectations. Quality in the car's production was based on the "craft team" concept, whereby a group of workers assembled the car at work stations rather than on a production line and personally signed to attest to its adherence to quality specifications. Hence, a more aggressive set of claims in the initial ads would be supported by product performance and quality.

Though the overall response to driving performance was good, respondents who categorized the Visala in categories 6 (Porsche 944) and 7 (BMW 300) rated it lower on performance than the typical cars in those categories. This finding suggests that attempts to position Visala as a high performance car are not likely to succeed. Therefore, the model simulation in Table 4 for performance sports car is not likely to be feasible on the basis of the responses to driving the Visala.

The categorization, elimination, consideration, and choice modeling suggests that the car be positioned as a sports car (category 5) and not as a personal luxury car (category 8), that luxury be secondary to the sporty image, and that the ads emphasize the quality and comfort features of the new car. With this marketing strategy, the model predicts sales of more than 70,000 units in four years.

[7]These probabilities were determined by examining the placement of the Visala car by 40 clinic participants who were shown an initial concept board for the car that identified it as extremely sporty rather than the base case "new kind of sports car" concept board.

Validation Issues

The Visala was introduced in the fall of 1988 behind advertising developed to highlight the Visala as a "new kind" of personal sports car. However, the launch plan used as input to the model to generate the forecast was not implemented as expected. Production was delayed and only a small number of cars were ready for selected dealers in September as showroom demos. Because of this shortage, introductory advertising for the Visala was terminated after two weeks. Eventually, 75% of the original fall advertising budget was spent to support another new model in the product line. When the production capacity increased to one half of the originally planned levels in December, the cars were shipped to dealers, but there was little advertising support (25% of plan). Inventories built up and dealers cut prices.

Needless to say, this launch was not well executed. Sales in the first model year were only 4500 versus predicted sales of 11,000 units. At the start of 1989, production was at planned levels and advertising spending was reinstated at the original year 2 levels. Dealer attitudes toward the car were not very positive. However, sales responded modestly to the marketing program and second year sales reached 7900 units, well below the predicted level of 16,300. New competition arrived in the form of the restyled Nissan 300ZX, Mitsubishi Eclipse, and new Mazda RX7 convertible. The original model assumptions underestimated the intensity of competition in the sporty two-seat car segment. At the end of 1989, 2000 cars were sold to auto rental companies at distress prices to reduce inventories. In 1990, the Visala was "relaunched" as a convertible model, with twice the original introductory advertising spending and new copy that stressed quality. Sales moved up modestly to 6500 units, but still fell much below the 20,300 units forecast for year 3. Competition in 1990 was even more intense, with the launch of the new Mazda Miata, the newly styled Toyota MR2, and other convertible models of existing cars such as the Toyota Celica. At the end of year 3, the Visala program was terminated because of low sales and increased demand on the production capacity to produce other autos.

When the actual execution of a launch is very different from the initial plan and competitive assumptions are in error, model validation is difficult. The original forecast must be adjusted to reflect these changes before the model's validity can be assessed.

The following adjustments to the model inputs were made to reflect observed departures from the original marketing program. These adjustments were based on judgments made by the Visala product manager and on results from subsequent market research studies.

1. Advertising was set to one half of plan for the first month, zero for the next two months, and to 25% of the plan for the remainder of the first year.
2. Conversion of purchase interest into actual sales at the dealer level was reduced by 20% to reflect the lack of trade commitment in year 1 and by 35% to reflect distress selling practices that began in late 1989.
3. Competitive pressures were increased by multiplying the original Visala forecast of sales by .9 for year 2 and .7 for year 3.
4. Year 3 advertising was increased to twice the introductory level to reflect the car's relaunch.

On the basis of these revised inputs, the model produced an adjusted forecast. Table 5 gives the actual sales data, the initial forecasts, and the forecasts adjusted for the changes in plan execution and competition. Though the original forecasts involved significant error (150% error in the three-year estimate of total sales), the error associated with the adjusted model was 3.1%. The yearly absolute forecast error was greater, averaging about 5%. Figure 4 displays the monthly forecasted (original and adjusted) and actual sales. This figure indicates large monthly deviations. The root mean square error is 244 units, or more than 40% of the average monthly sales level. If the primary interest in premarket forecasting is annual and life cycle sales levels, the model performs reasonably well, but recall that substantial judgment was required in setting the revised parameters.

Validation difficulties due to changes in plans and environment are not uncommon (e.g., Roberts and Urban 1988; Urban, Hauser, and Roberts 1990; Urban and Katz 1983), but in this application the adjustments were large. Further application experience will be required before the proposed model extension can be accepted as valid.

Further Research and Conclusion

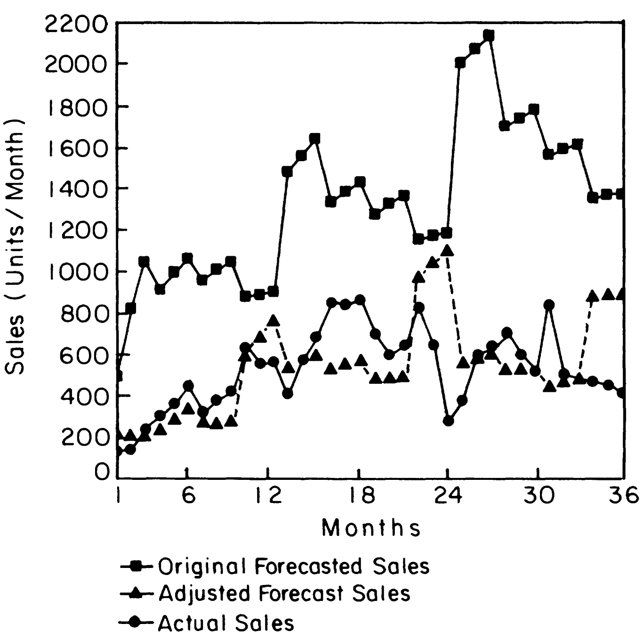
The submodel and measurement methodology for understanding the consumer decision steps of categorization, elimination, and consideration is described here in the context of a specific durable goods new product model, but it can be used or adapted whenever a model is conditioned on evoking or specific brand awareness. For example, the submodel could be added as a front end to either new product trial and repeat purchase or logit choice models in the packaged goods area (e.g., SPRINTER by Urban 1970; TRACKER by Blattberg and Golanty 1978; ASSESSOR by Silk and Urban 1978; and NEWS by Pringle, Wilson, and Brody 1982). Both ASSESSOR and NEWS are macro-flow models, with the same flow structure as the durable forecasting model described here. Therefore, it would be straightforward to integrate our results into either model. TRACKER, conjoint, and simple logit models would be more difficult to adapt to incorporate these

TABLE 5
Original, Actual, and Adjusted Sales Levels

Year	Original Forecast	Actual Sales	% Difference[a]	Adjusted Forecast	% Difference[b]
1	11,000	4,514	144.7	4,340	−3.9
2	16,300	7,905	106.2	7,890	−.2
3	20,300	6,549	207.6	7,370	+11.6
Total	47,600	19,018	150.2	19,600	+3.1

[a](original-actual)/actual
[b](adjusted-actual)/actual

FIGURE 4
Original Forecast, Adjusted Forecast, and Actual Monthly Sales



ideas. The Ben-Akiva and Boccara (1990) two-stage logit model is an alternative approach to the choice problem. However, their individual-level probability model of consideration and choice has very high input demands. Our approach could help restrict the two-stage logit to a smaller set of subcategories, or supply the complete first stage on an aggregate basis if measures were not feasible for the complete individual-level model. A link could also be made between our categorization model and measurement methodology and the Bass-like life cycle models (e.g., Mahajan, Muller, and Bass 1990). An initial approach here would involve estimating the three-parameter life cycle model for each category on the basis of customer sorting inputs and aggregate modeling.

The categorization extension we propose would be useful for product classes in which the number of alternatives is large and consumers are likely to use a simplifying choice heuristic. Though the inclusion of a categorization module is not likely to produce dramatic increases in forecasting accuracy, it would make possible a much richer strategic analysis. By designing the product and introductory strategy to target both the best subcategory and the positioning within it, sales and profits may be significantly increased.

Our model shows sales will vary substantially on the basis of consumer categorization of a new product, but we did not explore the reasons for a car's elimination. One area of research interest is the identification of categorization cues and an assessment of their influence on the categorization process. Individual consumers might be asked to describe verbally in detail the typical car identified for each pile formed, and to explain why specific piles were eliminated. In addition, one could make changes in attribute information for the new product in a more systematic fashion to assess the impact of individual attribute information items on categorization.

A major issue raised in our work is the quality of the aggregation represented in the model. Though individual differences in categorization, elimination, and consideration are incorporated explicitly into the proposed model, we assume in our discussion that there is only one true market structure. For example, in the case of the Visala application, all individuals perceive exactly nine distinct categories of automobiles. Alternatively, an individual model of the process could be developed, with aggregation at the individual rather than at the aggregate level as proposed here (e.g. Urban, Hauser, and Weinberg 1991).

The model we describe represents an attempt at integrating behavioral science with quantitative managerial modeling to improve marketing strategy formulation. The use of behavioral science theories in management science models undoubtedly presents many problems that researchers might not otherwise face, but the potential promise of such integrated efforts is great. Much more work needs to be done in bringing together the behavioral and quantitative models to improve marketing decision making.

Appendix A

For many consumer durable goods, consumers reduce the risk of making a wrong choice by searching for relevant information (advertising, magazine review) and visiting dealers to see products. They are also likely to ask other consumers about their purchases (word-of-mouth communication). Hence, it is important for consumer durable goods manufacturers to track the influence of their marketing activities on the total set of information consumers receive.

The probabilistic model proposed by Urban, Hauser, and Roberts (1990) explicitly keeps track of these consumer information flows. Each consumer is represented by a behavioral state that describes his or her level of information about his or her potential purchase. The behavioral states are chosen to represent consumer behavior as affected by managerial decisions.

In each time period, consumers flow from one state to another. The flow model keeps track, probabilistically, of the market, but does not track individual consumers. The flow probabilities are estimated from clinic results or managerial experience. The clinic format, which provides measures of consumers' reactions to various information items for the new product, generally includes a control group that evaluates an existing product. The model structure is based, in part, on differences between the test and control groups and the (known) sales history for the whole product category.

In some cases the flow rates (percentage of consumers per period) are parameters, say X% of persons who are aware via ads visit dealers in any given period. In other cases, the flows are functions of other variables. For example, the percentage of unaware consumers who become aware in a period is clearly a function of advertising expenditures. The exact functions used for a given application are chosen as flexible yet parsimonious parameterized forms. Whenever possible, they are justified by more primitive assumptions or are based on experience in other categories.

A detailed discussion of the flow equations embodied in a flow model such as the one in Figure 1 is beyond the scope of our article, but is provided by Urban, Hauser, and Roberts (1990). However, Table A1 lists the flows shown in Figure 1 and indicates the data sources used to estimate these flows. Parameters α, β, γ, δ, λ, and θ are unknowns, but generally are based on managerial experience and judgment.

Appendix B

The following hypothetical example shows how one individual forms several piles and how the information in those piles reveals that individual's categorization, elimination, and consideration processes. Suppose the individual is handed a deck of 20 cards, with choice alternatives numbered from 1 to 20. The familiarity set for this individual consists of 17 alternatives (numbers 1 through 17; therefore $n_f = 17$), and the cards representing these alternatives are then sorted by the individual into five piles (see Figure B1). The resulting piles range in size from a minimum of two alternatives to a maximum of five. For this individual, the consideration set consists of alternatives 1, 3, 4, 7, and 14 (i.e., $n_c = 5$). This consideration set spans four of the five piles formed. Furthermore, one of the piles contains two consideration set members whereas three

TABLE A1
New Inputs and Sources for Model

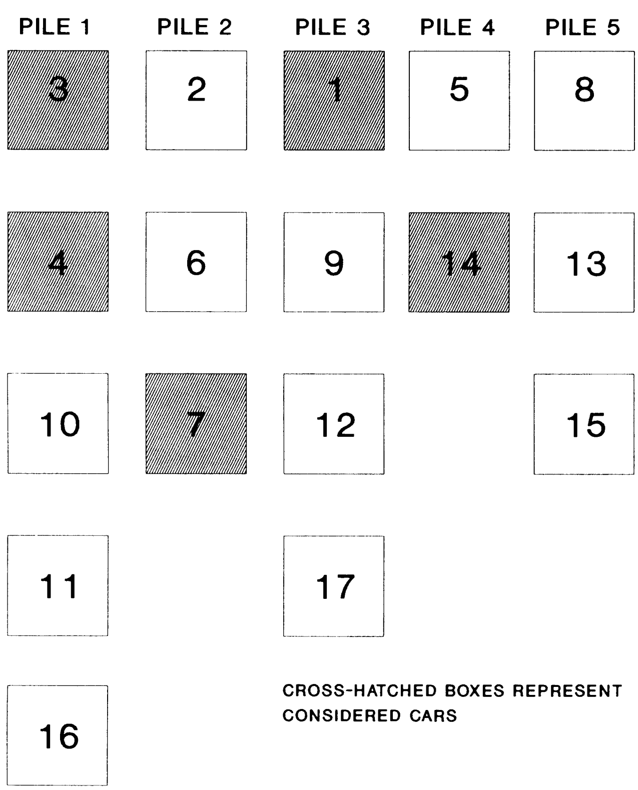
Input	Source
Target Group Size	Set in plan for number of buyers
Category Sales (monthly)	Econometric forecasts
Awareness	
Advertising spending (monthly)	Planned levels
α, β, forgetting (flow from aware of ad, W-O-M, or both to unaware)	Fit to past awareness, spending, and sales for control car, and modify judgmentally for changes for new car
In Market	
Fraction of persons aware who are in market	Calculate as category sales divided by target group size for all awareness conditions
Visit Dealer	
Fraction who visit dealer given ad aware	Clinic measured probability of purchase after ad exposure
Fraction who visit dealer given ad and W-O-M aware	Clinic measured probability of purchase after W-O-M videotape exposure
Fraction who visit dealer given W-O-M aware	Judgmentally set given preceding two values
Purchase	
Probability of buying new car given awareness condition:	
1. ad aware before visit and no other awareness	Clinic measured probability of purchase after ad exposure and test drive
2. ad aware before visit and W-O-M	Clinic measured probability of purchase after ad, test drive, and W-O-M exposure
3. ad and W-O-M aware before visit	Clinic probability of purchase after ad, W-O-M, and test drive
4. ad aware before and after visit	Judgmentally set on basis of 1, 2, and 3
5. W-O-M aware before and no other awareness	Judgmentally set on basis of 1, 2, and 3
6. W-O-M before and after visit	Judgmentally set on basis of 1, 2, and 3
Word-of-Mouth Communication	
ρ, γ	Managerial judgment of fit to past data on fraction of awareness due to W-O-M and control car sales
δ	Past survey data, judgment, and fit to control car sales

TABLE A1
Continued

Input	Source
Aware of ads and W-O-M	Probability of ad aware times probability of W-O-M aware
Production	
γ, θ	Managerial judgment, fit to past data on control car sales, and past research studies
Fraction of buyers who want to buy "off the lot"	Past studies and judgment

A complete technical appendix detailing all flow equations employed in the Visala application (as described in the text) can be obtained from the first author.

FIGURE B1
Individual Piles



other piles each contain one. If we define a "consideration pile" as any pile containing one or more members of the consideration set, four of the five piles formed by this individual are consideration piles and pile 5 is eliminated (i.e., $n_e = 3$; $n_e' = 9$). By the logic of the decision model described in the text, a new product categorized as belonging to any one of the four consideration piles would be examined further, but a new product categorized in the fifth pile would be eliminated from further consideration.

For the individual's responses represented in Figure B1, equations 2 through 4 in the text result in the following calculations.

$$P(E) = 3/17 = .176$$
$$P(\bar{E}) = .824$$
$$P(C|\bar{E}) = 5/(17 - 3) = .357$$
$$P(C) = P(C|\bar{E})P(\bar{E}) = .294.$$

That is, an average new brand in this hypothetical product category has an 18% chance of being eliminated outright, a 36% chance of consideration given nonelimination at the outset, and an overall consideration probability of 29%.

We are assuming, however, that all categories are equally likely to be chosen for the new product. It is more likely that a consumer will perceive some categories to be more appropriate for the new brand than others. That is, it is necessary to keep separate track of each of the categories formed by the individual. In this case, the category indicator j would range in value from 1 to 5. For the information represented in Figure B1, equation 5 would then yield the following consideration probability.

$$\begin{aligned} P(C) = {} & (5/5)(2/5)(5/17) + (3/3)(1/3)(3/17) \\ & + (4/4)(1/4)(4/17) + (2/2)(1/2)(2/17) \\ & + (0/3)(0/3)(3/17) = 2/17 + 1/17 \\ & + 1/17 + 1/7 + 0/17 = .294 \end{aligned}$$

This is the same probability of consideration calculated above. However, cars placed in pile 1 are more likely to receive consideration than those placed in any of the other piles. Though this information appears obvious at the individual level, it is far from obvious after aggregation across individuals.

Now consider the aggregate cluster results in Table B1, based on the same product class example used in Figure B1. Though the individual in the example is familiar with only 17 of the 20 available products, the aggregate clusters include all 20 alternatives. In this case, the number of aggregate clusters is also smaller than the number of piles formed by the individual, as shown in Figure B1 (though for other individuals the number of aggregate clusters could be larger).

Using the aggregate cluster (or category) information in Table B1, we can apply the assignment rule described in the text for the person in our example. It should be clear by now that this assignment will depend on where the card for the new product is placed. For example, if the card is placed in pile 1, it is perceived as similar to two category 1 alternatives (item numbers 3 and 4), two category 2 members (numbers 10 and 11), and one category 4 member (number 16). By the assignment rule, the new alternative would be randomly assigned for

TABLE B1
Hypothetical Aggregate Categories

Category 1	Category 2	Category 3	Category 4
1	5	13	15
2	6	14	16
3	7		17
4	8		18
	9		19
	10		20
	11		
	12		

this person to either aggregate category 1 or aggregate category 2. In contrast, if the card for the new product is placed in pile 2, it is perceived as similar to one category 1 item (number 2) and two category 2 items (numbers 6 and 7). The new product would be assigned unambiguously to aggregate category 2 for this individual. Similarly, if the individual places the card for the new product in piles 3, 4, or 5, the new item will be assigned to aggregate category 2, to either aggregate category 2 or aggregate category 3, or to one of aggregate clusters 2, 3, or 4, respectively.

REFERENCES

Alba, Joseph W. and Amitava Chattopadhyay (1985), "Effects of Context and Part-Category Cues on Recall of Competing Brands," *Journal of Marketing Research*, 22 (August), 340–9.

Barsalou, Lawrence W. (1985), "Ideals, Central Tendency, and Frequency of Instantiation as Determinants of Graded Structure," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 11 (October), 629–54.

Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science*, 15 (5), 215–27.

Ben-Akiva, Moshe and Bruno Boccara (1990), "Discrete Choice Models With Latent Choice Sets," working paper, Center for Transportation Studies, Massachusetts Institute of Technology.

Blattberg, R. and J. Golanty (1978), "TRACKER: An Early Test Market Forecasting and Diagnostic Model for New Product Planning," *Journal of Marketing Research*, 15 (May), 192–202.

Gensch, Dennis (1987), "A Two Stage Disaggregate Attribute Choice Model," *Marketing Science*, 6, 223–31.

Green, Paul E. and V. Srinivasan (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," *Journal of Consumer Research*, 5 (September), 103–23.

Guadagni, Peter M. and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (Summer), 203–38.

Hauser, John R., Glen L. Urban, and John H. Roberts (1983), "Forecasting Sales of a New Consumer Durable," in *Advances in Practices of Marketing Science*, Fred S. Zufryden, ed. Los Angeles: University of Southern California, Los Angeles, 115–28.

———— and Birger Wernerfelt (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16 (March), 393–408.

Howard, John A. and Jagdish N. Sheth (1969), *The Theory of Buyer Behavior*. New York: John Wiley & Sons, Inc.

Lussier, Dennis A. and Richard W. Olshavsky (1979), "Task Complexity and Contingent Processing in Brand Choice," *Journal of Consumer Research*, 6 (September), 154–65.

Mahajan, Vijay, Eitan Muller, and Frank M. Bass (1990), "New Product Diffusion Models in Marketing: A Review and Directions for Research," *Journal of Marketing*, 54 (January), 1–26.

Massy, William F., David B. Montgomery, and Donald G. Morrison (1970), *Stochastic Models of Buying Behavior*. Cambridge, MA: The MIT Press.

McFadden, Daniel (1980), "Econometric Models of Probabilistic Choice," in *Structural Analysis of Discrete Data With Econometric Applications*, F. Manski and D. McFadden, eds. Cambridge, MA: The MIT Press.

Park, C. Whan and Daniel C. Smith (1989), "Product-Level Choices: A Top-Down or Bottom-Up Process?" *Journal of Consumer Research*, 16 (December), 289–99.

Parkinson, Thomas L. and Michael Reilly (1979), "An Information Processing Approach to Evoked Set Formation," in *Advances in Consumer Research*, Vol. 6, W. L. Wilkie, ed. Miami: Association for Consumer Research, 227–32.

Payne, John W. (1976), "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior and Human Performance*, 16, 366–87.

————, James R. Bettman, and Eric J. Johnson (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 534–52.

Pringle, L. G., R. D. Wilson, and E. I. Brody (1982), "NEWS: A Decision-Oriented Model for New Product Analysis and Forecasting," *Marketing Science*, 1 (Winter), 1–29.

Ratneshwar, S. and Allan D. Shocker (1991), "Substitution-in-Use and the Role of Usage Context in Product Category Structures," *Journal of Marketing Research*, 28 (August), 281–95.

Roberts, John H. (1989), "A Grounded Model of Consideration Set Size and Composition," in *Advances in Consumer Research*, Vol. 16, Thomas S. Srull, ed. Provo, UT: Association for Consumer Research, 749–57.

———— and James M. Lattin (1991), "Developing and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28 (November), 429–40.

———— and Glen L. Urban (1988), "Modeling Multiattribute Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice," *Management Science*, 34 (February), 167–85.

Silk, Alvin J. and Glen L. Urban (1978), "Pre-Test-Market Evaluation of New Packaged Goods: A Model and Measurement Methodology," *Journal of Marketing Research*, 15 (May), 171–91.

Srivastava, Rajendra K., Robert P. Leone, and Allan D. Shocker (1981), "Market Structure Analysis: Hierarchical Clustering of Products Based on Substitution-in-Use," *Journal of Marketing*, 45 (Summer), 38–48.

Sujan, Mita (1985), "Consumer Knowledge: Effects on Evaluation Strategies Mediating Consumer Judgments," *Journal of Consumer Research*, 12 (June), 31–46.

———— and James R. Bettman (1989), "The Effects of Brand Positioning Strategies on Consumers' Brand and Category Perceptions: Some Insights From Schema Research," *Journal of Marketing Research*, 24 (November), 454–67.

Urban, Glen L. (1970), "Sprinter Mod III: A Model for the Analysis of New Frequently Purchased Consumer Products," *Operations Research*, 18 (5), 805–54.

————, John R. Hauser, and John H. Roberts (1990), "Prelaunch Forecasting of New Automobiles," *Management Science*, 36 (4), 401–21.

———, ———, and Bruce D. Weinberg (1991), "Information Acceleration and New Production Auto Forecasting," paper presented at the 1991 TIMS-Marketing Science Conference (March 21), Wilmington, DE.

———, Philip L. Johnson, and John R. Hauser (1984), "Testing Competitive Market Structures," *Marketing Science*, 3 (Spring), 83–112.

——— and Gerard M. Katz (1983), "Pre-Test-Market Models: Validation and Managerial Implications," *Journal of Marketing Research*, 18 (August), 221–34.

Reprint No. JM572103

LINKED CITATIONS

Premarket Forecasting for New Consumer Durable Goods: Modeling Categorization, Elimination, and Consideration Phenomena

Glen L. Urban; John S. Hulland; Bruce D. Weinberg

Journal of Marketing, Vol. 57, No. 2. (Apr., 1993), pp. 47-63.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28199304%2957%3A2%3C47%3APFFNCD%3E2.0.CO%3B2-7

[Footnotes]

[2] **Testing Competitive Market Structures**
Glen L. Urban; Philip L. Johnson; John R. Hauser
Marketing Science, Vol. 3, No. 2. (Spring, 1984), pp. 83-112.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198421%293%3A2%3C83%3ATCMS%3E2.0.CO%3B2-H

[3] **Market Structure Analysis: Hierarchical Clustering of Products Based on Substitution-in-Use**
Rajendra K. Srivastava; Robert P. Leone; Allan D. Shocker
Journal of Marketing, Vol. 45, No. 3. (Summer, 1981), pp. 38-48.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28198122%2945%3A3%3C38%3AMSAHCO%3E2.0.CO%3B2-5

[3] **Testing Competitive Market Structures**
Glen L. Urban; Philip L. Johnson; John R. Hauser
Marketing Science, Vol. 3, No. 2. (Spring, 1984), pp. 83-112.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198421%293%3A2%3C83%3ATCMS%3E2.0.CO%3B2-H

NOTE: *The reference numbering from the original has been maintained in this citation list.*

LINKED CITATIONS

[5] **Testing Competitive Market Structures**
Glen L. Urban; Philip L. Johnson; John R. Hauser
Marketing Science, Vol. 3, No. 2. (Spring, 1984), pp. 83-112.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198421%293%3A2%3C83%3ATCMS%3E2.0.CO%3B2-H

References

Effects of Context and Part-Category Cues on Recall of Competing Brands
Joseph W. Alba; Amitava Chattopadhyay
Journal of Marketing Research, Vol. 22, No. 3. (Aug., 1985), pp. 340-349.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28198508%2922%3A3%3C340%3AEOCAPC%3E2.0.CO%3B2-1

A New Product Growth for Model Consumer Durables
Frank M. Bass
Management Science, Vol. 15, No. 5, Theory Series. (Jan., 1969), pp. 215-227.
Stable URL:
http://links.jstor.org/sici?sici=0025-1909%28196901%2915%3A5%3C215%3AANPGFM%3E2.0.CO%3B2-4

Tracker: An Early Test Market Forecasting and Diagnostic Model for New Product Planning
Robert Blattberg; John Golanty
Journal of Marketing Research, Vol. 15, No. 2. (May, 1978), pp. 192-202.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197805%2915%3A2%3C192%3ATAETMF%3E2.0.CO%3B2-O

A Two-Stage Disaggregate Attribute Choice Model
Dennis H. Gensch
Marketing Science, Vol. 6, No. 3. (Summer, 1987), pp. 223-239.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198722%296%3A3%3C223%3AATDACM%3E2.0.CO%3B2-A

LINKED CITATIONS

Conjoint Analysis in Consumer Research: Issues and Outlook
Paul E. Green; V. Srinivasan
The Journal of Consumer Research, Vol. 5, No. 2. (Sep., 1978), pp. 103-123.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28197809%295%3A2%3C103%3ACAICRI%3E2.0.CO%3B2-5

A Logit Model of Brand Choice Calibrated on Scanner Data
Peter M. Guadagni; John D. C. Little
Marketing Science, Vol. 2, No. 3. (Summer, 1983), pp. 203-238.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198322%292%3A3%3C203%3AALMOBC%3E2.0.CO%3B2-S

An Evaluation Cost Model of Consideration Sets
John R. Hauser; Birger Wernerfelt
The Journal of Consumer Research, Vol. 16, No. 4. (Mar., 1990), pp. 393-408.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28199003%2916%3A4%3C393%3AAECMOC%3E2.0.CO%3B2-6

Task Complexity and Contingent Processing in Brand Choice
Denis A. Lussier; Richard W. Olshavsky
The Journal of Consumer Research, Vol. 6, No. 2, Special Issue on Consumer Decision Making. (Sep., 1979), pp. 154-165.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28197909%296%3A2%3C154%3ATCACPI%3E2.0.CO%3B2-B

New Product Diffusion Models in Marketing: A Review and Directions for Research
Vijay Mahajan; Eitan Muller; Frank M. Bass
Journal of Marketing, Vol. 54, No. 1. (Jan., 1990), pp. 1-26.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28199001%2954%3A1%3C1%3ANPDMIM%3E2.0.CO%3B2-7

Product-Level Choice: A Top-Down or Bottom-Up Process?
C. Whan Park; Daniel C. Smith
The Journal of Consumer Research, Vol. 16, No. 3. (Dec., 1989), pp. 289-299.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28198912%2916%3A3%3C289%3APCATOB%3E2.0.CO%3B2-U

LINKED CITATIONS

News: A Decision-Oriented Model for New Product Analysis and Forecasting
Lewis G. Pringle; R. Dale Wilson; Edward I. Brody
Marketing Science, Vol. 1, No. 1. (Winter, 1982), pp. 1-29.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198224%291%3A1%3C1%3ANADMFN%3E2.0.CO%3B2-W

Substitution in Use and the Role of Usage Context in Product Category Structures
S. Ratneshwar; Allan D. Shocker
Journal of Marketing Research, Vol. 28, No. 3. (Aug., 1991), pp. 281-295.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28199108%2928%3A3%3C281%3ASIUATR%3E2.0.CO%3B2-5

Development and Testing of a Model of Consideration Set Composition
John H. Roberts; James M. Lattin
Journal of Marketing Research, Vol. 28, No. 4. (Nov., 1991), pp. 429-440.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28199111%2928%3A4%3C429%3ADATOAM%3E2.0.CO%3B2-R

Modeling Multiattribute Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice
John H. Roberts; Glen L. Urban
Management Science, Vol. 34, No. 2. (Feb., 1988), pp. 167-185.
Stable URL:
http://links.jstor.org/sici?sici=0025-1909%28198802%2934%3A2%3C167%3AMMURAB%3E2.0.CO%3B2-C

Pre-Test-Market Evaluation of New Packaged Goods: A Model and Measurement Methodology
Alvin J. Silk; Glen L. Urban
Journal of Marketing Research, Vol. 15, No. 2. (May, 1978), pp. 171-191.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197805%2915%3A2%3C171%3APEONPG%3E2.0.CO%3B2-P

Market Structure Analysis: Hierarchical Clustering of Products Based on Substitution-in-Use
Rajendra K. Srivastava; Robert P. Leone; Allan D. Shocker
Journal of Marketing, Vol. 45, No. 3. (Summer, 1981), pp. 38-48.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28198122%2945%3A3%3C38%3AMSAHCO%3E2.0.CO%3B2-5

NOTE: *The reference numbering from the original has been maintained in this citation list.*

LINKED CITATIONS

Consumer Knowledge: Effects on Evaluation Strategies Mediating Consumer Judgments
Mita Sujan
The Journal of Consumer Research, Vol. 12, No. 1. (Jun., 1985), pp. 31-46.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28198506%2912%3A1%3C31%3ACKEOES%3E2.0.CO%3B2-R

The Effects of Brand Positioning Strategies on Consumers' Brand and Category Perceptions: Some Insights from Schema Research
Mita Sujan; James R. Bettman
Journal of Marketing Research, Vol. 26, No. 4. (Nov., 1989), pp. 454-467.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28198911%2926%3A4%3C454%3ATEOBPS%3E2.0.CO%3B2-M

Sprinter Mod III: A Model for the Analysis of New Frequently Purchased Consumer Products
Glen L. Urban
Operations Research, Vol. 18, No. 5. (Sep. - Oct., 1970), pp. 805-854.
Stable URL:
http://links.jstor.org/sici?sici=0030-364X%28197009%2F10%2918%3A5%3C805%3ASMIAMF%3E2.0.CO%3B2-P

Prelaunch Forecasting of New Automobiles
Glen L. Urban; John R. Hauser; John H. Roberts
Management Science, Vol. 36, No. 4. (Apr., 1990), pp. 401-421.
Stable URL:
http://links.jstor.org/sici?sici=0025-1909%28199004%2936%3A4%3C401%3APFONA%3E2.0.CO%3B2-N

Testing Competitive Market Structures
Glen L. Urban; Philip L. Johnson; John R. Hauser
Marketing Science, Vol. 3, No. 2. (Spring, 1984), pp. 83-112.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198421%293%3A2%3C83%3ATCMS%3E2.0.CO%3B2-H

Pre-Test-Market Models: Validation and Managerial Implications
Glen L. Urban; Gerald M. Katz
Journal of Marketing Research, Vol. 20, No. 3. (Aug., 1983), pp. 221-234.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28198308%2920%3A3%3C221%3APMVAMI%3E2.0.CO%3B2-D

NOTE: *The reference numbering from the original has been maintained in this citation list.*