A DYNAMIC ATTRIBUTE SATIATION MODEL OF VARIETY SEEKING BEHAVIOR*

by
Leigh McAlister**

Sloan W.P. No. 1283-82 September 1981

THE MARKETING CENTER

Massachusetts Institute of Technology
Alfred P. Sloan School of Management
50 Memorial Drive
Cambridge, Massachusetts 02139
(617) 253-6615

A DYNAMIC ATTRIBUTE SATIATION MODEL OF VARIETY SEEKING BEHAVIOR*

by
Leigh McAlister**

Sloan W.P. No. 1283-82 September 1981

*The author wishes to acknowledge the financial support provided by the University of Washington Graduate School of Business Summer Research Fund and the valuable guidance of Professor James Bettman of UCLA in stimulating, developing and presenting these ideas.

**Visiting Assistant Professor of Management Science, Alfred P. Sloan School of Management, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139

A DYNAMIC ATTRIBUTE SATIATION MODEL
OF VARIETY SEEKING BEHAVIOR

ABSTRACT

This paper presents a model of individual consumer choice behavior for separate choice occasions. Contrary to the popular notion that each choice is essentially independent of its predecessors, that very dependence is proposed as the key to variety seeking behavior. From the consumption history one can infer which valued attributes the subject has recently consumed and in what quantities. Comparing this to the ideal amount of each attribute for that subject gives an indication of the attribute combination that would be most preferred by that subject at that point in time. As the consumption history evolves, the pattern of attribute accumulations will change, leading to preference for items rich in different attributes at different points in time. The model is operationalized and specific parameterizations are inferred from a collection of soft-drink consumption diaries. The proposed model is shown to predict choices better than a model which ignores the dependence among choices.

A Dynamic Attribute Satiation Model of Variety Seeking Behavior

INTRODUCTION

An excerp from a soft drink consumption diary indicates that the subject drank a Coke on Monday, a Coke on Tuesday, a Dr. Pepper on Wednesday, a 7-Up on Thursday, a Pepsi on Friday and a Club Soda on Saturday. Further questioning of the subject reveals that Dr. Pepper was selected on Wednesday because it was offered that day at an especially low price. Seven-Up was chosen Thursday as a change of pace. The subject wanted a Coke on Friday but settled for a Pepsi because Coke was not available. Saturday night the subject chose Club Soda to mix in her Scotch drink.

This pattern of switching among brands is not atypical for frequently purchased, non-durable goods. Switching can be induced by the manipulation of marketing variables, by the accessibility of the product, by the situation in which the product is consumed or by the desire for variety. It is switching for the sake of variety with which this paper is concerned. In particular, it is proposed that such switching is not completely random. A deterministic process which would lead to variety-seeking is proposed, modelled and empirically tested. The process differs from traditional models in its consideration of the impact of previous selections.

The hypothesized effect of consumption history on variety seeking is based on three assumptions. Following Lancaster (1971) it is assumed that items can be represented by the values they take on for their constituent attributes. Similarly, a collection of items can be represented by the sum of values, across items in the collection, on those constituent attributes.

A consumption history, which is a collection of items, can therefore be represented by the attribute accumulations or attribute "inventories" it generates.

Consider the simplified example in Tables 1 and 2. Individual soft drinks are described by the two attributes fruit flavor and caffeine. At any point in time, the consumption history can be summarized by the amounts of those two attributes that have been accumulated. On day 1 only one Coke has been consumed so the accumulated inventories would be 2 units of fruit flavor and 9 units of caffeine. The consumption of another Coke on day 2 would raise the inventories by 2 and 9 units respectively. After the consumption of a Dr. Pepper on day 3 the fruit flavor inventory would be incremented by 5 units and the caffeine inventory by 7 units, etc.

[Tables 1 and 2 About Here]

The second assumption concerns the continual depletion of the inventories through physiological processing or forgetting. This depletion can be conceptualized as the discounting of older consumption experiences. That is, the soft drink that a subject consumed a week ago has a smaller residual impact on her current attribute inventories than one she consumed yesterday. Similarly, that soft drink she consumed yesterday would have a smaller residual impact than one she consumed one hour ago. Figure 1 describes the ups and downs of the inventory of caffeine generated by the consumption history in Table 2. From day to day the inventory drops by half[1] to represent the physiological processing or forgetting of the attribute. With each consumption there is a discrete jump upward in the level of the inventory equal in size to the amount of the attribute in the soft drink consumed.

[Figure 1 About Here]

Finally, it is assumed that there is a decreasing marginal relationship between the attribute inventories that would result from the consumption of a particular item and preference for that item. Figure 2 depicts two possible decreasing marginal relationships:[2]

1) A finite ideal point that lies within the achievable range of the attribute inventory (given by the dashed curve).
2) A finite ideal point that lies beyond the achievable range of the attribute inventory (given by the broken curve).

Consider a single attribute. When the inventory of that attribute is very low this assumption implies that preference for a unit of that attribute is at its highest. As the inventory of that attribute grows, perference per unit drops. Should the inventory reach its ideal level or point of satiation, the marginal impact of adding a unit of the attribute is zero. Beyond the point of satiation, preference decreases. This phenomenon explains why a cola might be very appealing at times (when the inventory of caffeine is low and therefore the marginal impact on preference of adding to that inventory is relatively high) and less so at other times (when the inventory is high implying that additions will have a relatively small marginal impact on preference).

[Figure 2 About Here]

The amalgamation of these three assumptions is a dynamic attribute satiation process. It holds that preference for an item at a point in time is a function of the preference contributions of that item's constituent attributes. The preference contribution of each attribute is, however, a function of the consumption history (summarized by attribute inventories) and the point of satiation for that attribute. Since the configuration of attribute inventories can change dramatically as the consumption history

evolves, it is not surprising that shifts in preferences among choice alternatives (and resulting variety seeking) are observed.

In this paper the dynamic attribute satiation process is operationalized as an estimatable model. Soft-drink consumption diaries are used to infer individual specific parameterizations of that model. The ability of the proposed model to predict actual choices is shown to be superior to that of a model based on the assumption that each choice is independent of prior selections. The managerial implications of this finding are discussed.

LITERATURE REVIEW

As mentioned earlier, brand switching is sometimes induced by the manipulation of marketing variables (price, product design, promotion, distribution) and sometimes by changes in situational variables. Early studies of brand loyalty (Tucker 1964, McConnell 1968) and a similar study in social psychology (Brickman and D'Amato 1975) controlled for these factors and still reported switching. In those studies subjects were asked to make repeated choices from a set of unfamiliar stimuli. Two distinct phases of switching behavior were apparent in the data. Initially, subjects systematically explored the stimuli. Later in the experiment, subjects tended to alternate among the elements of their favored subset of the stimuli. Much of the consumer behavior literature on variety seeking, novelty seeking, innovativeness, etc. focuses on switching like that of the first phase (e.g., Robertson 1971, Venkatesan 1973, Hirschman 1980). This phase can be distinguished[3] from the later one by the information acquisition motive. It is switching like that of the second phase (switching among familiar items that is done simply for "variety") with which this paper deals.

Bass, Pessemier and Lehman (1972) studied choice from a familiar product class controlling the impact of marketing and situational variables. Subjects in their study chose the brand they reported as their favorite only about half the time. The authors attributed the switching to and among reportedly less preferred brands to "a stochastic component of choice which arises because of variety seeking" (Bass, Pessemier and Lehmann 1972, p. 538). This line of reasoning gave rise to Bass' (1974) "Theory of Stochastic Preference and Brand Switching". According to that theory, relative preferences dictate the proportion of times each brand is chosen. Any particular selection, however, is at the mercy of a "stochastic element in the brain". Blin and Dodson (1980) propose a specific functional relationship between the frequency with which a brand will be chosen and the importance weights in an individual's linear compensatory preference function. In a variation on this theme Huber and Reibstein (1978) propose that the item selected is a deterministic function of parameters of the preference function of the person doing the choosing. Those parameters, however, are assumed to change in a random fashion.

Under the theory of stochastic preference, variety seeking is viewed as non-understandable. Other paradigms allow explanation of the phenomenon. Predominant among the explanations is the notion of "optimal arousal" (Berlyne 1960, Hansen 1972). Individuals are hypothesized to select that collection of items which will provide just the right amount of stimulation or arousal. Optimal arousal is frequently conceptualized as a single peaked relationship (Coombs and Avrunin 1977) between preference and the stimulation provided by the collection selected. McAlister (1979) modelled the stimulation provided by the collection as a function of the stimulation provided by attributes of items in the collection. Her model predicts the collection of items a person would select at a point in time.

Jeuland (1978) modelled variety seeking behavior across time. He essentially proposed item (i.e., brand) specific stimulation optima. He further proposed "inventories" of item stimulation which evolve dynamically in a manner analogous to the just described evolution of attribute inventories. Implicit in this formulation is the assumption that the consumption of one item has no impact on the inventories of other items. As pointed out by Hagerty (1980), this ignores the effect of item similarity. Under Jeuland's model the preference for Coke should not be affected by consuming either (Pepsi, Dr. Pepper, RC Cola, Pepsi) or (7-Up, 7-Up, 7-Up, Mountain Dew, Sprite). Changes in preference result from changes in the relevant inventory and in either of these cases the inventory of Coke would be zero.

In the proposed dynamic attribute satiation process inventories of attributes rather than inventories of items are accumulated. The first consumption history above would generate a large inventory of caffeine and a small inventory of fruit flavor. The second consumption history would generate a large inventory of fruit flavor and a small one of caffeine. The evaluation of the caffeine and fruit flavor contributions of a Coke (and hence the evaluation of Coke itself) will probably be very different with the first consumption history than it would be with the second.

OPERATIONALIZING THE DYNAMIC ATTRIBUTE SATIATION MODEL

Consistent with models in the traditions of Fishbein (1963) and Lancaster (1971), the Dynamic Attribute Satiation (DAS) model relates preference for an item to the preference contributions of the attributes of that item. Assuming there are no interactions among the attributes,[4] preference for an item will be defined as the sum of the contributions to

preference made by each of the attributes. That is:

$$DAS_{Tk} = \sum_{j=1}^{J} P_{Tkj} \qquad (1)$$

where DAS_{Tk} = preference for item k at time T assigned by the Dynamic Attribute Satiation model,

J = the number of attributes over which items are described,

P_{Tkj} = contribution of attribute j to the level of satisfaction that would result from consuming object k at time T.

The contribution of attribute j to satisfaction from consuming object k at time T, P_{Tkj}, is assumed to be a function of the inventory of attribute j at time T, the ideal level of attribute j, and the amount of attribute j in object k. It was argued that the particular functional relationship should be marginally decreasing with a single optimum at the ideal point. A quadratic relationship of the form presented in Equation (2) displays these properties and is easily estimated.[5]

$$P_{Tkj} = w_j \, [(I_{Tj} + X_{kj}) - \hat{X}_j]^2(-1) \qquad (2)$$

where P_{Tkj} = contribution of attribute j to the level of satisfaction that would result from consuming object k time T,

w_j = importance weight for attribute j,

I_{Tj} = inventory of attribute j at time T,

X_{kj} = amount of attribute j in object k,

$\hat{X}_j$ = ideal level for attribute j.

Note that when the current inventory of attribute j plus the amount of attribute j in object k $(I_{Tj} + X_{kj})$ exactly equals the ideal for attribute j $(\hat{X}_j)$, the term which is squared equals zero forcing P_{Tkj} to also equal zero. The more $I_{Tj} + X_{kj}$ differs from $\hat{X}_j$, the more negative P_{Tkj} becomes. That is, preference peaks at the ideal point. To either add to or diminish the inventory reduces overall preference.

Attribute Inventory

The attribute inventory is hypothesized to dwindle continuously and experience discrete increments each time an item containing that attribute is consumed (see Figure 1). A similar process was proposed by Little and Lodish (1969) for the cumulative impact of advertising and by Jeuland (1978) for the evolution of "experience" with a brand. The particular functional form used here to convert a consumption history ($X_{k_t j}$, t=1, 2, ..., T) into an inventory is given by Equation 3.

$$I_{Tj} = \sum_{t=1}^{T} \lambda_j^{T-t} X_{k_t j} \qquad (3)$$

where I_{Tj} = inventory of attribute j at time T,

λ_j = inventory retention factor for attribute j, $0 \leq \lambda \leq 1$,

k_t = item chosen at time t,

$X_{k_t j}$ = amount of attribute j in the item chosen at time t.

The speed with which the inventory dwindles is an inverse function of the inventory retention factor, λ_j. It seems reasonable that this factor might differ across individuals and across attributes. For instance, one might expect $\lambda_{\text{thirst quenching}}$ for athletically active persons to be smaller than $\lambda_{\text{thirst quenching}}$ for more sedate persons, indicating a more rapid dwindling of the inventory of thirst quenchingness for athletically active persons than for the more sedate. (In general the λ's for heavy users of a product class might be expected to be lower than λ's for light users.) Similarly, one might expect $\lambda_{\text{calories}} > \lambda_{\text{carbination}}$ for an individual indicating that the human body divests itself of carbonation more rapidly than calories.

Unfortunately, the estimation procedure employed requires the <u>a priori</u> specification of values for the λ_j's. Receiving no guidance on the

selection of such values from those who have proposed similar processes (Little and Lodish 1969; Jeuland 1978) the value for λ_j was set arbitrarily at 1/2 for all attributes and all individuals.[6] This arbitrary selection will impede the predictive ability of DAS. However, the objective of this paper is to demonstrate that a process which considers the interdependence of choices has greater predictive ability than one which views each choice as independent of all others. If the process incorporating the interdependence (DAS) is able to make better predictions in spite of a handicap in parameter selection, the point will be made. Future research into the pattern of variation of these parameters should provide insights useful to researchers and managers and enhance the predictive ability of such models.

Parameters of the Model

Ideal Points. It is important to note that the ideal points in the DAS model, ($\hat{X}_j$: j = 1, 2, ..., J), do not necessarily reflect the amount of attribute j that one would like to find in a single choice alternative. Rather, they indicate the optimal level for the entire inventory of that attribute. As the inventory level of an attribute decreases, the amount of that attribute which is desired in a choice alternative increases.

Importance Weights. The difference between an inventory retention factor and an importance weight should be noted. An importance weight reflects the degree of disutility associated with being a given number of units from one's ideal level. Comparisons among importance weights allow one to make statements concerning the relative impact of each attribute assuming that all else is held constant. But all else is not held constant, and inventory retention factors determine the pattern of that inconstancy. For example, being one unit away from one's ideal level of thirst quenchingness might be less unpleasant than being one unit away from the ideal level of sweetness

(importance weight for sweetness > importance weight for thirst quenchingness). However, if this individual's $\lambda_{\text{thirst quenchingness}}$ and $\lambda_{\text{sweetness}}$ were such that the inventory of thirst quenchingness depleted much more rapidly than the inventory of sweetness, alternatives offering relatively more thirst quenching ability than sweetness would probably be chosen. This in spite of the fact that sweetness has a higher importance weight than thirst quenching ability.

Confounding of Parameter Estimates when Inventory is Ignored.

If people do, in fact, evaluate choice alternatives relative to the current state of their attribute inventories, one might expect bias to be introduced by estimation procedures which do not account for those inventories. In an appendix to this paper it is shown that the failure to account for inventories will not bias importance weights but will bias ideal points. The direction of ideal point bias will be downward from the true ideal by an amount equal to the inventory at that point in time. For that instant the bias in the parameter exactly makes up for the failure to include inventory in the stimulus-attribute matrix. At later points in time the inventory will be at different levels and the parameter's bias will not exactly compensate. The managerial implications of this bias will be explored in the "Discussion of Findings" section.

DATA

Data for the study reported in this paper were collected between October and December, 1978. Twice in the course of this 81 day study (at the beginning and half way through) subject perceptions of stimuli on relevant attributes were elicited. Twice a week during the course of this study, subjects were asked to rank order the stimuli from most preferred to least

preferred and to report all items from the stimulus product class that they consumed since they last gave data. Data from the first 50 days of the study is used to estimate parameters of different models. These estimated models are then employed to predict actual choices made during the last 30 days of the study. Statistics based on those predictions allow comparison of models.

Subject Population

The subjects in this study were 36 graduate and undergraduate students enrolled in the School of Business Administration at the University of Washington during Fall Quarter, 1978. Twenty-two percent of the subjects were females. No economic incentive was offered for participation in the study. Motivation for accurate reporting of information was provided by having the professor in a bi-weekly class begin each period by distributing data collection forms and requesting that serious thought be given to the task. Responses to a questionnaire administered at the end of the study indicate that subjects were neither intrigued nor irritated[7] by the tasks and tended to report their preferences accurately.[8]

Stimuli

This study, as did Bass, Pessemier and Lehamann's (1972), deals with preferences for and choices among soft drinks. The 10 stimuli selected were: Coke, Diet Pepsi, Dr. Pepper, Mountain Dew, Pepsi, Royal Crown Cola, 7-Up, Sprite, Sugar Free 7-Up and Tab. These soft drinks were reported in Standard and Poor's Industry Survey (1978) as having the ten highest market shares, ranging from a share of 26.6% for Coke down to 1.2% for Sugar Free 7-Up. The total of market shares for stimulus soft drinks is 69.2% with no excluded soft drink receiving more than .9% of the market. These soft drinks include 6 colas and 4 non-colas and 3 diet drinks and 7 non-diet drinks.

The subjects were, on average, reasonably familiar with this product class. Their self reported familiarity with the stimulus soft drinks,

averaged across subjects and across soft drinks, is 2.8 on a scale on which 1 indicates that the subject had never tasted the soft drink and 5 indicates that the subject often drinks it.

The attributes selected to describe the stimulus soft drinks are the same as those used in the Bass, Pessemier and Lehmann (1972) study: carbonation, calories, sweetness, thrist quenching ability, and popularity with others.[9] Seventy-two percent of the subjects indicated that they thought that the selected attributes were not the only factors they considered in selecting a soft drink. Other attributes that they mentioned as important include (in order of frequency of mention, most frequent first): taste, price, availability, caffeine, saccharine, can size and nutrition.

Data Collection Instrument

The data collection instrument was made up of three documents. The first document, administered at the beginning of the study and half way through, elicited subject perceptions of attribute values for stimulus soft drinks on 6 point scales (0 to 5). Zero indicated that the brand possessed virtually none of the attribute. Five indicated that the brand possessed a great deal of the attribute. The order in which stimulus soft drinks were presented was randomized across subjects.

The second document, administered bi-weekly for the 11 weeks of the study, elicited a history of soft drink consumption since the subject last gave data. It also requested that the ten stimulus soft drinks be rank ordered from the brand a subject would most like to consume at that point in time to the brand she would least like to consume at that point in time. The order of presentation of soft drinks for the rank-ordering task was randomized across data collection occasions.

The final document was administered at the end of the study to survey subjects' attitudes about the study. It included questions regarding familiarity with the stimuli, involvement with the experimental tasks, reasons

for selecting a soft drink other than the one which had most recently been reported as most preferred and factors other than experimental attributes that influenced the subject's selection of soft drinks.

Model Estimation

The algorithm LINMAP was used to estimate parameters for DAS. Because not all subjects reported preferences at every possible data collection opportunity (due to class absences, etc.) the number of preference reports per subject in days 1-50 of the study (the time period used to estimate parameters) ranges from 5 to 11. Their respective stimulus-attribute matrices were therefore made up from 50 to 110 stimuli (10 from each report, corresponding to the perceptions of the 10 stimulus soft drinks augmented by the inventories). This does not, however provide the information content of a single ranking of 50 to 110 objects. Since no comparisons were made across report periods, it is impossible to say whether the stimulus ranked third on one day is more or less preferred than one ranked fifth on another day. The information content of the 50 to 110 stimuli was estimated[10] and the measures were considered sufficient to confidently estimate the 12 parameters (an ideal point and importance weight for each of the six attributes).

Two versions of an alternative model which treated each choice as independent of all others were also estimated using LINMAP. Under this paradigm, attribute inventories did not need to be considered. Therefore the stimulus set facing subjects on each data collection occasion was considered identical. Their multiple reports of preference rankings were then viewed as replications of the same task. The two versions of this alternative model were distinguished by the dependent variables used in their estimation. One was based on the ranking from the first preference report given by a subject. The other was based on a ranking consistent with the average, across preference reports, for that subject.

RESULTS

Two types of tests were utilized to assess the performance of DAS relative to a model which does not incorporate the impact of past choices. Goodness of fit tests deal with the models' relative abilities to replicate the preference reports (from the first half of the study) which were used in their estimation. The external validity test compares the models with respect to their ability to predict actual choices made during the second half of the study.

The statistics used for the goodness of fit comparisons are the Kendall's taus reported by LINMAP in estimating the models' parameters. These statistics measure the correlation between the actual preference reports and the preference ranking predicted by the estimated model. They are compared in three different ways in Table 3. Column 1 reports the average value for τ across subjects. Column 2 reports the percentage of the subjects for whom the value of τ is greater than .8. Column 3 reports the percentage of subjects whose reported preferences correlate more highly with model predictions than with the average preference ranking (interpreting the study based market shares as an average preference ranking). The measure of external validity (reported in column 4 of Table 3) is the percentage of actual choices made which were correctly predicted by the various models.

[Table 3 About Here]

Among the three models estimated (DAS, Independent Choices based on the First Preference Report, and Independent Choices based on the Average Preference Report), DAS dominates on all measures. Tests for the statistical significance of the differences between the average τ for DAS and those of the two variants of the Independent Choices model are significant at the .01

level. The difference between the two variants of the Independent Choices model is not significant, even at the .1 level. These tests are summarized as follows:

Difference	Average Across 36 Subjects	Standard Deviation	t-statistic
τDAS - τIndependent Choices, 1st Pref	.09	.19	2.80
τDAS - τIndependent Choices, Avg. Pref	.11	.18	3.62
τIndependent Choices, 1st Pref - τIndependent Choices, Avg. Pref.	.02	.14	.85

τ_{35} (.01) = 2.44

τ_{35} (.1) = 1.31

DISCUSSION

From the statistics just reported, one can infer that, for these subjects, DAS reproduces preferences and predicts choices better than a model which does not consider past choices. This can be taken as evidence that the inventorying process outlined in this paper is an important determinant of choice behavior. Under that assumption, several issues deserve further consideration.

It was shown that estimates of ideal points are biased when models are estimated without regard for attribute inventories. The interpretation of this bias depends on the wording of statements which elicit the rank ordering used in estimating parameters. The two forms of questioning typically employed have to do with reporting "preferences at this point in time" or "preferences generally."

The first form of questioning will elicit biases equal to the current inventories of the attributes. Model reestimation at different points in time

could very well yield radically different values for ideal points. (Perhaps it was observation of some such phenomenon that led Huber and Reibstein (1978) to hypothesize their random ideal points model.) Each estimated ideal point would be biased by an amount equal to the level of inventory at the time the rank-ordering was elicited. A model so estimated should do a good job of predicting choice behavior at that particular point in time. As inventories dwindle and are replenished, however, the preference ranking will very likely change.

The second form of questioning ("preferences generally") will elicit biases equal to average inventories of attributes. These biases, contrasted with those just discussed, should be relatively stable. Model reestimation at different points in time should yield similar values for ideal points. Unfortunately, there is no guarantee that this model will reflect the true preference ranking for any particular choice occasion. For example, on a given choice occasion one might have a very high inventory of sweetness, suggesting the choice of a non-sweet object. By the next choice occasion the inventory of sweetness could have dwindled dramatically making a very sweet object appealing. Preferences based on average inventory level would suggest choice of a moderatley sweet object. In fact the one non-sweet object and one very sweet object were chosen.

The importance of attribute inventories suggests a new class of model parameters, inventory retention factors, to be investigated. Although the values for all inventory retention factors for all subjects in this study were taken to equal 1/2, arguments have been offered concerning the likely variability of those parameters. In summary, it has been proposed that the inventory retention factors are determined by underlying physiological and/or psychological processes. For example, inventory of "sweetness" might be analogous to blood sugar level. The inventory retention factor would be,

in that case, a function of the body's ability to metabolize sugar. Inventory retention factors for non-physiologically based attributes like "popularity with others" or "stylishness" might be a function of self-confidence, innovativeness or similar psychological constructs. Given these systemic roots for the factors, hypotheses concerning the patterns of values across populations and across time can be posited and tested.

The results of such studies should have far-reaching managerial implications. It will be important to eliminate or at least understand the biases caused by ignoring inventories. Designing new products or repositioning old ones on the basis of ideal points derived from models which do not consider inventories could be dangerous for the reasons outlined above. It could be similarly misleading to segment the population based on importance weights alone. While the weights are not biased by estimation procedures which ignore inventories (see appendix), they alone do not tell the whole story. For example, sweetness might be twice as important to person A as to person B. But, if their inventory retention factors indicated that person B's inventory would drop 6 times faster than that of person A, relative choice behavior might be counter to expectation based on importance weights alone.

Even more important than those specific implications, consideration of attribute inventories may provide the manager with a clearer understanding of the process by which consumers make choices. It would seem that this better understanding should aid the manager in all aspects of marketing her product.

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

As proposed in the introduction, the Dynamic Attribute Satiation (DAS) Model is simply one more step in the process of explaining individual choice behavior. Consideration of the impact of situational variables in predicting

individual choice has improved that prediction (e.g., Warshaw 1980). While this is surely a step forward, it is not the end of the process. In the Bass, Pessemier and Lehmann (1972) study, situational factors were controlled and switching among brands was still observed. DAS was designed specifically to accomodate that non-situationally based switching. The version of the DAS model empirically tested in this paper was able to expand prediction beyond that of a model which does not account for the impact of the consumption history. This is especially encouraging since the inventory retention factors, which are the key to encoding the effect of the consumption history in DAS, were only crudely approximated. Exploration of these parameters should further improve the predictive ability of the model and provide valuable insight into the process by which individuals make choices.

Further research into the nature of the inventory retention factors and the sensativity of predictive ability to a wide range of values for those parameters should be done. Specific hypotheses linking inventory retention parameter values to demographic and psychographic variables should be explored. The estimation procedure used in this paper requires that values for the inventory retention factors be tested by trial-and-error. No convexity or even continuity properties can currently be attributed to the relationship between parameter values and predictive ability. Hence improvement can be noted but global optima cannot be guaranteed. Perhaps a reformulation of the inventory term (Equation 3) or the creative use of estimation procedures could solve this problem. Better estimation of parameter values should, in turn, lead to questions concerning the specific implications for different product classes and population segments.

The calculation of attribute inventories needs to be extended to acquisition of attributes from products overlapping the product class under study by one or more attributes. For example, the inventory of sweetness

relevant to the selection of soft drinks is affected not only by sweetness from historical soft-drink consumption, but also by historical consumption of cake, pie, fruit, etc. In general, any object consumed which has sugar content contributes to that inventory. The large number of items an individual consumes suggests that this extension may be difficult.

Finally, an attempt should be made to consolidate, within the multiattribute framework, the predictive progress made by considering situational factors with that made by considering consumption histories. By capturing these two factors simultaneously and detailing the ways in which they might affect one another, we should move yet one step further along the road to explaining individual choice behavior.

BIBLIOGRAPHY

Bass, Frank M. (1974), "The Theory of Stochastic Preference and Brand Switching," Journal of Marketing Research, 11 (February), 1-20.

_____________, Edgar A. Pessemier, and Donald R. Lehmann (1972), "An Experimental Study of Relationships Between Attitudes, Brand Preference and Choice," Behavioral Science 17 (November), 532-41.

Berlyne, D. C. (1960), Conflict, Arousal and Curiosity, New York: McGraw-Hill.

Blin, Jean-Marie and Joe A. Dodson (1980), "The Relationship Between Attributes, Brand Preference, and Choice: A Stochastic View," Management Science, Vol. 26, No. 6 (June) 606-19.

Brickman, Philip and Barbara D'Amato (1975), "Exposure Effects in a Free-Choice Situation," Journal of Personality and Social Psychology, Vol. 32, No. 3, 415-420.

Fishbein, Martin (1963), "An Investigation of the Relationship Between Beliefs About An Object and the Attitude Toward that Object," Human Relations, 16 (August), 233-40.

Green, Paul E. and V. Srinivasan (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," Journal of Consumer Research, 5 (September), 102-23.

Hagerty, Michael R. (1980), "The Situational Model: A Theory of Choice," Ph.D. Dissertation, The University of Illinois.

Hansen, Flemming (1972), Consumer Choice Behavior: A Cognitive Theory, The Free Press, New York.

Hirschman, Elizabeth C. (1980), "Innovativeness, Novelty Seeking, and Consumer Creativity," Journal of Consumer Research, Vol. 7, No. 3 (December), 283-95.

Huber, Joel and David J. REibstein (1978), "Attitude Measures and Choice Frequency: Some Pitfalls to be Avoided," in John C. Maloney, Attitude Research Plays for High Stakes; Chicago, American Marketing Association.

Jain, Arun K., Franklin Acito, Naresh K. Malhotra and Vijay Mahajan (1979), "A Comparison of the Internal Validity of Alternative Parameter Estimation Methods in Decompositional Multiattribute Preference Models," Journal of Marketing Research, 14 (August), 313-22.

Jeuland, Abel P. (1978), "Brand Preference Over Time: A Partially Deterministic Operationalization of the Notion of Variety Seeking," AMA Proceedings (August).

Kendall, Maurice (1962), Rank Correlation Methods. New York, Hafner Publishing Company.

Keon, John W. (1980), "The Bargain Value Model and a Comparison of Managerial Implications with the Linear Learning Model," Management Science, Vol. 26, No. 11 (November) 1117-30.

Lancaster, Kelvin (1971), Consumer Demand: A New Approach. New York: Columbia University Press.

Little, John D. C. and Leonard M. Lodish (1969), "A Media Planning Calculus," Operations Research, Vol. 17, No. 1 (January-February), 1-35.

McAlister, Leigh (1979), "Choosing Multiple Items from a Product Class," Journal of Consumer Research, 6 (December), 213-224.

McConnell, J. Douglas (1968), "The Development of Brand Loyalty," Journal of Marketing Research, 5 (February), 13-19.

Robertson, Thomas S. (1971), Innovative Behavior and Communication, Holt, Rinehart and Winston, Inc., New York.

Srinivasan, V. and Allan D. Shocker (1973), "Linear Programming Techniques for Multidimensional Analysis of Preferences," Psychometrica, 38 (September), 337-69.

Standard and Poor's (1978). Industry Surveys A-L, Vol. 1, (April).

Tucker, W. T. (1964), "The Development of Brand Loyalty," Journal of Marketing Research, (August), 32-35.

Venkatesan, M. (1973), "Cognitive Consistency and Novelty Seeking," in Scott Ward and Thomas S. Robertson, eds., Consumer Behavior: Theoretical Sources, Prentice-Hall, Inc., Englewood Cliffs, New Jersey, 355-384.

Warshaw, Paul R. (1980), "A New Model for Predicting Behavioral Intentions: An Alternative to Fishbein," Journal of Marketing Research, (May), 153-72.

FOOTNOTES

1 The fraction of the inventory which carries through from one day to the next might be any value from 0 to 1. In operationalizing the model it was necessary to select a particular value. One half was chosen arbitrarily. This issue is discussed further in the section on "Operationalizing the DAS Model".

2 A constant marginal relationship is also depicted in Figure 2 (the solid line). This relationship implies that each incremental unit of an attribute contributes equally to preference. It is reasonable to believe that some attributes will display such a relationship. They would not, however, contribute to the kinds of preference shifts of interest here.

3 Keon (1980) would disagree. He argues that switching among familiar items results from the desire to refresh one's memory and assure oneself that the usual selection is superior.

4 If there is reason to believe, _a priori_, that interactions exist between certain attributes, a new attribute, defined as the product of the interacting attributes, can also be used. With this augmentation of the attribute set, the interaction is accounted for and the proposed model is still valid.

5 The estimation procedure to be used is LINMAP. This algorithm selects values for the importance weights and ideal points so as to most closely replicate the original preference ordering. An option available to the algorithm is to set ideal point for a given attribute at infinity. In that case equation (2) degenerates into a simple linear relationship. (See Srinivasan and Shocker 1973, pp. 345-346).

6 Because of the nature of the data collected and the estimation procedure used, over an hour of CPU time was required to estimate the models presented in this paper. It would be informative to reestimate the models assuming different values for λ. Comparison of the predictive ability of such reestimated models would shed light on the nature of the inventory retention factor. However, because of the exorbitant data processing requirements, and because the results obtained with $\lambda = 1/2$ were sufficient to address the central hypothesis in this paper, such reestimation was foregone.

7 Subjects self-reported their level of interest in the tasks on a 1-5 scale on which 1 indicated that they were quite interested in reporting preferences and perceptions and 5 indicated that they were irritated by requests to report perceptions and preferences. The average value for this variable across subjects was 3.03.

8 Subjects self-reported the accuracy of their preference reports on a 1-5 scale on which 1 indicated that their preference reports were unrelated to their true preferences and 5 indicated that their preference reports exactly reflected their true preferences. The average value for this variable across subjects was 3.81.

[9] For purpose of analysis a sixth attribute, cola/non-cola was also used. Because the value of that dichotomous attribute was obvious for the stimulus soft drinks, it was not necessary to elicit subject perceptions concerning it.

[10] Two criteria were considered for measuring the information content of a rank ordering. The first is the number of inherent paired comparisons: a ranking of k objects implies k(k-1)/2 paired comparisons. This measure multiple counts many pieces of information that are apparent via transitivity. Consider a ranking of 4 objects; A, B, C and D. This ranking implies 4(3)/2 = 6 paired comparisons (A > B, A > C, A > D, B > C, B > D, C > D; where > means "is preferred to"). However, given that one knows A > B and B > C, it is redundant to say that A > C (assuming transitivity). The second proposed measure disregards the redundant paired comparisons. It holds that the number of pieces of information in a ranking of k objects is k-1 (1st > 2nd, 2nd > 3rd, ..., k-1st > kth).

According to Green and Srinivasan (1978), in selecting the number of stimuli necessary for accurate parameter estimation one should consider the ratio of (number of stimuli)/(number of parameters estimated). "Number of stimuli" in that calculation is analogous to the number of objects in a single rank ordering. The "number of parameters estimated" for a given subject in this study is 12 (an ideal point and an importance weight for each of the 6 attributes). The relevant ratio using the first measure of information content runs from a lower bound of 21/12 = 1.75 for the subject providing only 5 preference reports to an upper bound of 31/12 = 2.67 for those subjects providing 11 preference reports. Using the second measure of information content, the ratio runs from 46/12 = 3.83 to 100/12 = 8.33.

TABLE 1: SIMPLIFIED DESCRIPTION OF SOFT DRINKS

Soft Drink	Fruit Flavor	Caffeine
Coke	2	9
Dr. Pepper	5	7
7-Up	9	0
Pepsi	3	8
Club Soda	0	0

TABLE 2: HYPOTHETICAL CONSUMPTION HISTORY

AND RESULTING INVENTORY OF CAFFEINE

		Contents of Soft Drink Consumed in Period t				
Time Period (t)	Soft Drink Consumed in Period t	Fruit Flavor	Caffeine	Inventory from Period t-1	Discounted Inventory from Period t-1	Inventory at the end of Period t
1	Coke	2	9	--	--	9.0
2	Coke	2	9	9.0	4.5	13.5
3	Dr. Pepper	5	7	13.5	6.8	13.8
4	7-Up	9	0	13.8	6.9	6.9
5	Pepsi	3	8	6.9	3.5	11.5
6	Club Soda	0	0	11.5	5.8	5.8

TABLE 3: TESTS OF MODELS
(n = 36)

Model	I--------GOODNESS OF FIT--------I			EXTERNAL I-VALIDITY-I
	(Col. 1)	(Col. 2)	(Col. 3)	(Col. 4)
	Average τ (std. dev.)	Percent of τ's $\geq$ .8	Percent of τ's > Correlation of 1st Preference Report with Market Share	Percent of Choices Predicted Correctly
DAS	.75 (.19)	33	100	26
Independent Choices, 1st Pref	.67 (.16)	31	94	17
Independent Choices, Average Pref	.64 (.15)	22	89	15

FIGURE 1: INVENTORY OF CAFFEINE

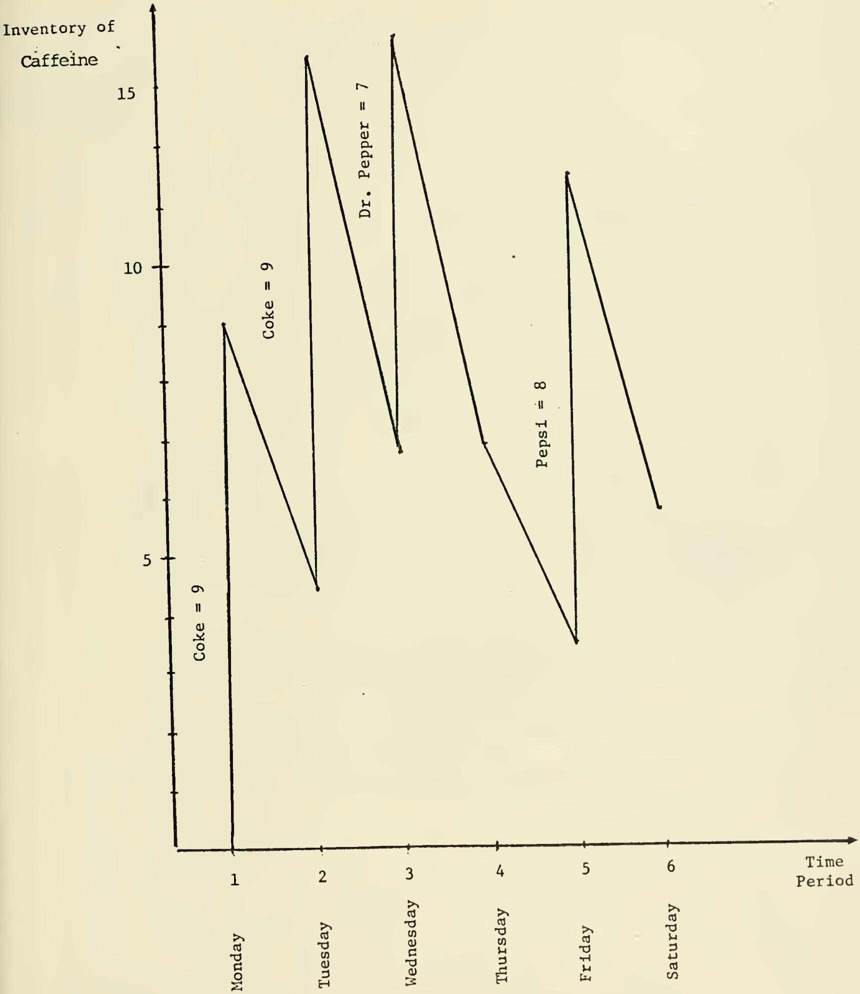
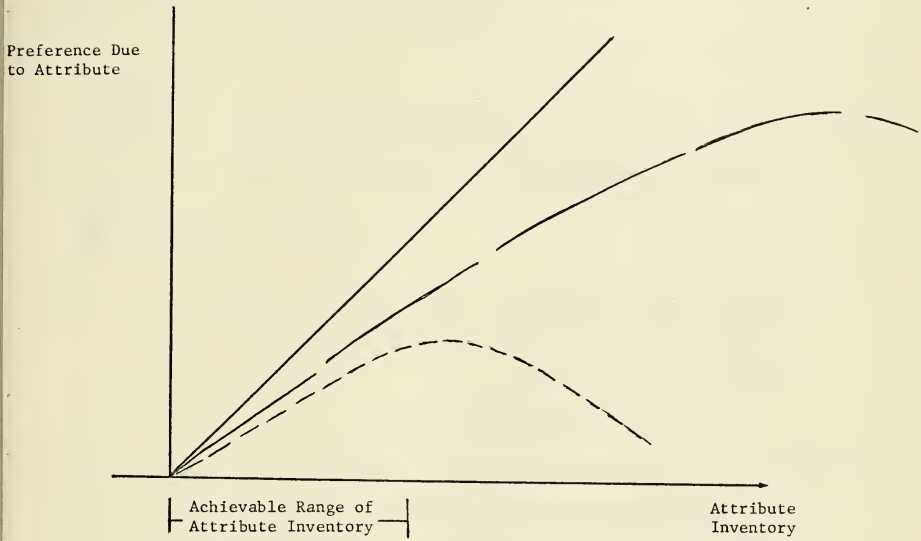


FIGURE 2: RELATIONSHIP BETWEEN ATTRIBUTE INVENTORY AND THE PREFERENCE CONTRIBUTION OF THAT ATTRIBUTE FOR FINITE AND INFINITE IDEAL POINTS



------ Preference for an Attribute with a Finite Ideal Point that Lies within the Achievable Range of the Attribute Inventory

— — Preference for an Attribute with a Finite Ideal Point that Lies beyond the Achievable Range of the Attribute Inventory

——— Preference for an Attribute with an Infinite Ideal Point

APPENDIX: THE INTRODUCTION OF BIAS IN PARAMETER ESTIMATES BY IGNORING INVENTORIES

Consider the contribution of attribute j from item k at time T when inventory is accounted for and when it is not:

INVENTORY ACCOUNTED FOR

$$P_{Tkj} = w_j\,[(I_{Tj} + X_{kj}) - \hat{X}_j]^2 \qquad (2)$$

(See the original statement of Equation 2 for the explanation of the terms.)

INVENTORY NOT ACCOUNTED FOR

$$\tilde{P}_{kj} = \tilde{w}_j\,[\tilde{X}_{kj} - \hat{\tilde{X}}_j]^2 \qquad (4)$$

where: $\tilde{P}_{kj}$ = contribution of attribute j to the satisfaction that would result from consuming object k, not accounting for inventory;

$\tilde{w}_j$ = importance weight for attribute j not accounting for inventory;

$\hat{\tilde{X}}_j$ = ideal level for attribute j not accounting for inventory.

With the proposed estimation procedure, these expressions would be incorporated in the constraints of LINMAP once for each paired comparison in which object k is involved. Consider a specific paired comparison: object k preferred to object k'. The related constraint accounting for inventory would imply that:

ACCOUNTING FOR INVENTORY:

$$\sum_{j=1}^{J} P_{Tkj} - \sum_{j=1}^{J} P_{Tk'j} + s_{kk'} \geq 0 \qquad (5)$$

where: J = the number of relevant attributes;

P_{Tkj} = contribution of attribute j to the satisfaction that would result from consuming object k at time T,

$\sum_{j=1}^{J} P_{Tkj}$ = satisfaction that would result from consuming object k at time T,

$s_{kk'}$ = artificial variable associated with the paried comparison (k,k'). (The sum of these artifical variables across all paired comparisons is the objective that LINMAP minimizes. It will equal zero if the paired comparison is satisfied. It will capture the magnitude of the violation otherwise.)

The constraint would take the following form if inventory were not accounted for:

$$\text{INVENTORY NOT ACCOUNTED FOR} \quad \sum_{j=1}^{J} \tilde{P}_{Tkj} - \sum_{j=1}^{J} \tilde{P}_{Tk'j} + \tilde{s}_{kk'} \geq 0 \tag{6}$$

where tilded variables are the "not accounting for inventory" counterparts of variables just described.

In order to state the "accounting for inventory" constraint in terms of the parameters to be estimated, substitute Equation (2) into Inequality (5) yielding:

ACCOUNTING FOR INVENTORY:

$$\sum_{j=1}^{J} [w_j (X_{kj}^2 - X_{k'j}^2) - \underbrace{2w_j (\hat{X}_j - I_{Tj})}_{v_j} (X_{kj} - X_{k'j})] + s_{kk'} \geq 0 \tag{7}$$

A similar substitution of Equation (4) into Inequality (6) and algebraic simplification yields the following constraint when inventory is not accounted for:

INVENTORY NOT
ACCOUNTED FOR:

$$\sum_{j=1}^{J} [\tilde{w}_j (X_{kj}^2 - X_{k'j}^2) - 2\tilde{w}_j \hat{\tilde{X}}_j (X_{kj} - X_{k'j})] + \tilde{s}_{kk'} \geq 0 \qquad (8)$$

$$\frac{I \qquad I}{\tilde{v}_j}$$

In the model not accounting for inventory, $\tilde{w}_j$ is estimated as the coefficient of $(X_{kj}^2 - X_{k'j}^2)$ and an artificial parameter, $\tilde{v}_j = -2\tilde{w}_j\hat{\tilde{X}}_j$, is estimated as the coefficient of $(X_{kj} - X_{k'j})$. The ideal point $\hat{\tilde{X}}_j$ is then inferred to equal $-1/2\left(\frac{\tilde{v}_j}{\tilde{w}_j}\right)$.

If the true process involves the evaluation of stimuli relative to an inventory, then reality is reflected in Inequality (7). Estimating the parameters with a model which doesn't account for inventory (Inequality 8), will yield $\tilde{w}_j$ and $\tilde{v}_j$ as coefficients of $(X_{kj}^2 - X_{k'j}^2)$ and $(X_{kj} - X_{k'j})$ respectively. From Inequality (7), then:

$$\tilde{w}_j = w_j \qquad (9)$$

$$\tilde{v}_j = -2w_j(\hat{X}_j - I_{Tj}) \qquad (10)$$

$$\hat{\tilde{X}}_j = -1/2\left(\frac{\tilde{v}_j}{\tilde{w}_j}\right) = \hat{X}_j - I_{Tj} \qquad (11)$$

From Equation (9) it is apparent that no bias is introduced into the importance weights by a model which doesn't account for inventory. Equation (11) shows that the ideal point estimated by a procedure not accounting for inventory is biased downward from the true ideal by an amount equal to the inventory at that point in time.

Date Due

MAY 1 1 1994

JUN 08 1994