



## **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>

*Operations Research* is currently published by INFORMS.

---

Your use of the JSTOR archive indicates your acceptance of JSTOR's Terms and Conditions of Use, available at <http://www.jstor.org/about/terms.html>. JSTOR's Terms and Conditions of Use provides, in part, that unless you have obtained prior permission, you may not download an entire issue of a journal or multiple copies of articles, and you may use content in the JSTOR archive only for your personal, non-commercial use.

Please contact the publisher regarding any further use of this work. Publisher contact information may be obtained at <http://www.jstor.org/journals/informs.html>.

Each copy of any part of a JSTOR transmission must contain the same copyright notice that appears on the screen or printed page of such transmission.

---

The JSTOR Archive is a trusted digital repository providing for long-term preservation and access to leading academic journals and scholarly literature from around the world. The Archive is supported by libraries, scholarly societies, publishers, and foundations. It is an initiative of JSTOR, a not-for-profit organization with a mission to help the scholarly community take advantage of advances in technology. For more information regarding JSTOR, please contact [support@jstor.org](mailto:support@jstor.org).

# SPRINTER MOD III: A MODEL FOR THE ANALYSIS OF NEW FREQUENTLY PURCHASED CONSUMER PRODUCTS

Glen L. Urban

*Massachusetts Institute of Technology, Cambridge, Massachusetts*

(Received January 28, 1969)

This paper presents a model-based information system designed to analyze test-market results, to assist decision-making for a new frequently purchased consumer product, and to serve as an adaptive control mechanism during national introduction. The model, called SPRINTER, is based on the behavioral process of the diffusion of innovation and can be used normatively in an interactive search mode to find the best marketing strategy for a new product. The input is obtained from test-market data analyzed by statistics and combined with subjective judgments. A GO, ON, or NO decision is made on the basis of the estimated profit and risk produced by the best marketing strategy. During national introduction the model serves as a 'problem-finding' mechanism. It uses early national sales and micro-level behavioral data to diagnose problems in the introduction. It also can be used to search for solutions to these problems as they are recognized. Finally, an application of this model to a real product is reported, this application using an on-line computer program that allows convenient man-system communication.

SINCE NEW products are frequently introduced and often fail, they provide a fertile subject for management science research. New products can provide sales and profit growth, but they are also risky, since their acceptance is difficult to predict. Since the key phenomenon is the diffusion of the innovation, a model that aspires to be useful in the analysis of new products should be based on the behavioral-science phenomena underlying the process. Models have been built to encompass the marketing strategy (see LEARNER,<sup>[19]</sup> URBAN<sup>[38]</sup>), risk (see CHARNES, ET AL.,<sup>[9]</sup> PESSIER,<sup>[28]</sup> Urban<sup>[38]</sup>), and information networks (see Charnes et al.,<sup>[8, 10]</sup> Urban<sup>[40]</sup>), and forecasting aspects of new product decisions (see HERNITER AND COOK,<sup>[16]</sup> MASSY<sup>[21]</sup>), but these models have not adequately modeled the basic diffusion and consumption process. Too, models have been developed at the micro-behavioral level (see AMSTUTZ,<sup>[1]</sup> Herniter and Cook<sup>[16]</sup>); although they have predictive capabilities, they have not been well adapted to searching for the best decision among the many strategy alternatives available—a capability that is necessary for a good analysis model.

The purpose of this paper is to describe a behaviorally based model that is useful in new-product introduction decisions. These include recommending strategies, specifying the GO (introduce)/ON (collect more information)/NO (reject) decisions for the product, and adaptively guiding the product through national introduction.

The concept of the diffusion of an innovation suggests that adoption of a new idea is not immediate and that some process accounts for the spread of its acceptance. The hypothesis is that a small segment of the population (called innovators) adopts an idea first; and then the idea spreads to others as the innovators pass information to them, as others observe the result of the innovator's acceptance, or as the others are exposed to mass-media communication and accept the idea without direct contact with an innovator. The diffusion of innovation has a very large literature, but the number of conclusions and generalizations about the process are few. While a diffusion process can describe the over-all growth in acceptance, the individual's decision to accept the innovation must also be considered. The development of awareness, attitudes, and preference must be specified. These should then be linked to higher functions such as the intent to purchase and search, and, finally, to product selection. After purchase, the behavioral processes of forgetting and interpersonal communication should be considered. The model described in this paper will include the basic diffusion phenomena within the purchase-decision sequence and link the controllable new-product variables to this process. Then alternate strategies can be evaluated, and meaningful forecasts of sales and profits generated.

The model is part of a larger entity that includes data, analysis, and computing capabilities, and that may be termed an information system; specifically, it contains: (1) a data bank of information relevant to the product, (2) a bank of statistical programs to analyze and interpret the data, (3) an input/output facility capable of communicating to managers, and (4) the market-response model. The heart of the system is the model, since it links the controllable variables to the response process, and so aids decision making. The system data base is pre-test and test-market data. A set of flexible multivariate analysis routines make up the statistical bank. The input/output capabilities can be supplied by an on-line computer system and a conversational program.

In the present case, the model is called *SPRINTER* Mod III, an acronym for *Specification of P*ROfits with *I*NTERdependencies. This model-based system is designed to serve as a means of (1) gaining meaningful behavioral interpretations from test-market data, (2) forecasting national sales levels before national introduction, (3) recommending improved product strategies, (4) recommending a GO, ON, or NO decision, and (5) identify-

ing national introduction problems, recommending solutions to them, and generating revised sales forecasts.

Having defined these goals for the system, this paper will next consider the model's specific development criteria, the basic behavioral process, and the mathematical model statements. Then the heuristic search procedure and the adaptive model properties will be presented. All considerations of input and parameter estimation are reserved until after this mathematical model discussion, but readers may find it useful to look ahead to Table I as they read the equations if they have measurement questions. The paper closes with a discussion of the initial application of the model.

### BEHAVIORAL-PROCESS MACROMODEL

#### *Model-Development Criteria*

In developing an information-system model, explicit design criteria should be set. The introductory section of this paper has already specified the criterion of high behavioral content, but there are a number of ways of satisfying this goal. One method is to build a micro-analytic simulation such as Amstutz;<sup>[1]</sup> a model of this type may contain 1000 market subunits and specify in minute detail the purchase decision in each unit. Another form of model might be an aggregate set of multivariate equations such as Learner's<sup>[19]</sup> consumer-product model or Urban's<sup>[38]</sup> industrial-product model, but these more aggregate models are limited in their ability to consider behavioral phenomena. In deciding on a level of detail for a new-product model, the ease of estimation, testing, and solution must also be considered; in general, it decreases as the level of detail increases, and drops sharply at the simulation microlevel. However, as the level of detail increases, the behavioral content and ability to describe consumers increases with a rapid increase at the microlevel. To determine the best level of modeling detail, the decision problem and the constraints on the modeling must be considered. If the firm has a large budget and no time or personnel constraints, the model can assume any level. In this case, the desired level of problem-solving detail dictates the best modeling level. The new-product analysis and decision problem posed in this paper argues for a more microscale model, since it is desirable to include the behavioral content of the adoption process and the problem requires detailed output.

The model will represent a hypothesis of how the market operates, so it will have to be relatively complex to allow the basic marketing interdependencies to be considered; this ability is especially important in gaining usage by managers. The model should represent a statement of the manager's implicit model. The model, in fact, will be much more powerful than the implicit model, but it should also have face validity to the decision

maker who is to use it. To achieve this face validity, a more microscale model is needed. In most new-product cases, the budget and time constraints will preclude a microsimulation, but will justify a model with a reasonably high level of detail if it can generate solutions to the marketing-mix problem and lend itself to testing and estimation. Such a model will fall between the simulation and aggregate-equation alternatives. This type of model may be called a 'behavioral macroprocess' model. This model can have a high level of behavioral content and face validity, but it will be feasible to develop and operate on a limited budget.

The basic approach in the behavioral macroprocess model is to model the flow process, but to do it at an aggregate level. The model will define mutually exclusive and collectively exhaustive states for groups of people. These groups will then flow to other new states. This flow is modeled by multiplying the number in the group by the fraction that will move to a particular new group. The final output state is purchase. The number buying in a given period will be the same as the expected value obtained from a large Monte Carlo simulation of the same process, if the covariance of the group size and the fraction defining movement is zero. This property of the model allows policy implications to be obtained by one run of the model rather than a number of runs as required in the Monte Carlo analysis. The macromodel determines the average value, while a Monte Carlo analysis gives a sample result and usually allows only a test for effect (e.g., an F-test) unless a large number of simulations is run (e.g., more than ten).

In addition to the efficiency gained by the aggregate average flows, the level of detail is reduced by other aggregations. For example, the model allocates its detail toward 'our' brand and aggregates competitors unless they specifically influence our brand through competitive effects. Another example is in the definition of periods. The model requires the period to represent the shortest purchase interval, since no more than one purchase will be allowed per period. Since purchase frequencies fall over a continuum, the period will represent an aggregation of some users with slightly varying purchase frequencies. Usually the period is defined as the interval between purchasers of 'heavy users;' for example, people who buy toothpaste every two weeks may be a meaningful definition of the heavy user. As a final example of the macrocharacteristics of the model, the consideration of various market segments is suppressed. Although heterogeneous segments may exist, they are initially aggregated into one group and considered by their average characteristics. Segments can be defined in the model, but they increase the cost of running it and collecting input data, so management must decide if the additional detail is worthwhile on a cost/benefit basis.

With the goal of achieving efficiency and behavioral content in mind, a behavioral macroprocess new-product model will now be described, first, by defining the steps in the consumption process verbally, then by describing these steps for several classes of customers, and, finally, by specifying mathematically the model phenomena and the effects of controllable variables on the process.

### ***Behavioral Processes***

The basic process elements of the model are (1) awareness, (2) intent, (3) search, (4) choice, and (5) post-purchase behavior. In the awareness section of the model consumers are classified on the basis of their awareness of the brand, advertisements, specific product appeals, and word-of-mouth communication. Awareness states are defined as exclusive hierarchical divisions: that is, people who are classed as brand-aware are only brand-aware; people who are ad-aware are brand- and ad-aware, but not aware of any appeals; people classed as aware of a specific appeal of the product are aware of the brand, ad, and that specific appeal, but no other appeals. Empirically, the assignment of people to these classes is based on a recall of the brand, ad, appeal, or a word-of-mouth recommendation. Thus, selective perception and selective forgetting can operate, since different people may recall different appeals after seeing the same ad. The distribution of people in the awareness classes reflects the effects of advertising expenditures in a given period, past advertising, product experience, and past receipt of word-of-mouth communication.

With these states of awareness defined, the next section of the model determines the number of these people who will have a predisposition to take action. This is called the intent element, and it takes each awareness-state population and processes it to determine how many people from the group will display preference for the brand and intent to purchase it. The percent of people in a given awareness class who display intent to buy the product depends on the perceived compatibility and relative advantage of the product to the people who have the specific recall of that class. Although the model does not possess a specific learning mechanism such as posited by KRUGMAN,<sup>[17, 18]</sup> or PALDA,<sup>[27]</sup> it does monitor the over-all behavioral response to advertising through the awareness to intent response. It would be expected that the percent with intent would be higher in appeal-recall classes than in the brand-awareness class, since specific appeal recall represents more perception of the product's relative advantage. The highest buying rates might be expected in the awareness states representing receipt of word-of-mouth recommendations, since this group is one in which the perceived risk is low. Empirically, the intent, or predisposition for action, can be measured by a direct question such as "Do you definitely

intend to buy this brand again?" or by indirect methods such as scales that use statements ranging from "I wouldn't use that brand even if you gave it to me!" to "I would look all over town for it." In the intent section and the previous awareness section, care has been taken to avoid direct dependence on attitude measurement. Rather, the process has been monitored by the more measurable specific recall and the more relevant predisposition to act.

After the number of people intending to buy has been determined for each awareness class, the populations of each class are added to get the total number of people with intent. These people now undertake a search effort in an attempt to find the product.

The search section of the model determines if the product is found at the consumer's favored retail store. This availability is based on the percent of distribution obtained by direct company and wholesaler sales effort when given a particular middleman margin or 'deal.' If the brand is not available, the consumer may delay choice and search at a different store.

If the product is available, the consumer with intent will choose the brand unless he is switched to another brand in the store. Switching is dependent upon the relative price and point-of-sale activity of the brand. The consumers with no intent before entering the store may purchase the brand on the basis of the instore price, promotion, and communication. If they purchase, they are added to the buyers who exercise their intent.

If a consumer buys a product, he may generate word-of-mouth recommendations, or can respond to word-of-mouth inquiries by nonbuyers. These exchanges are particular in content, and receivers are moved to new awareness and appeal classes on the basis of receipt of new information and its internalization. After each period, consumers experience forgetting. They forget selectively from one appeal-awareness class to another, so cognitive dissonance can be considered. After the completion of these post-purchase phenomena of word of mouth and forgetting, the consumers in each awareness state are returned to the awareness section of the model for the receipt of new communication and a repeat of the consumption cycle. As the cycle is repeated, the model's parameters such as trial rate are allowed to change so that the nonstationarity of buyer response can be encompassed.

### ***Brand Experience Classes***

The five-step behavioral process just outlined takes place in each of five experience classes of the model, these classes representing different levels of experience with the product (*see* Fig. 1). The first is the potential-trial class. All potential consumers of the basic type of product who have

not tried our brand of the product are in this potential-trial class. The total number of potential buyers of the product class is influenced by the combined communication and promotion effort of the firms in the industry. Consumers leave the potential trial class by a trial purchase of our brand of the product and move to the preference class. In the preference class, the consumer develops and displays his preference by additional purchases of our brand. If the new product is purchased again, the consumer moves to the loyalty I class where he either displays loyalty by a purchase of our brand and moves to the loyalty II class, or makes a purchase of a competitive brand and moves to the nonloyal class. The loyalty II class is formulated so that 'hard core' loyals can be isolated. To enter loyalty II, a consumer must have purchased our brand at least three times. The non-loyal class is made up of people who presumably have a loyalty for com-

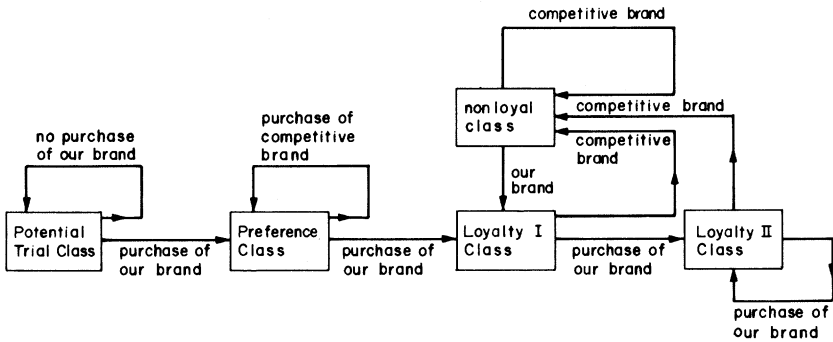


Fig. 1. Depth-of-class effects.

petitive brands. Return to loyalty I from the nonloyal class can be made by another purchase of our brand.

As the diffusion process proceeds, more people will leave the trial class and move on to the preference and loyalty classes. The rate of diffusion will depend on the trial rate of the innovators and their post-purchase behavior. As other adopters approach first purchase, the trial rate may fall. The degree of acceptance will ultimately depend upon the repeat-purchase behavior in the preference and loyalty classes, if we assume the trial rate is greater than zero. A successful product is characterized by a fast diffusion rate and a high degree of acceptance.

**Mathematical Model**

With this basic verbal description of the model, the mathematical detail of the potential trial, preference, and loyalty classes can be more readily understood. Over-all flow diagrams are included as a pedagogic

aid. Not all of the some five hundred equations of the model are included. However, each basic type of equation is described and a deliberate effort has been made to be complete enough so that other model builders can

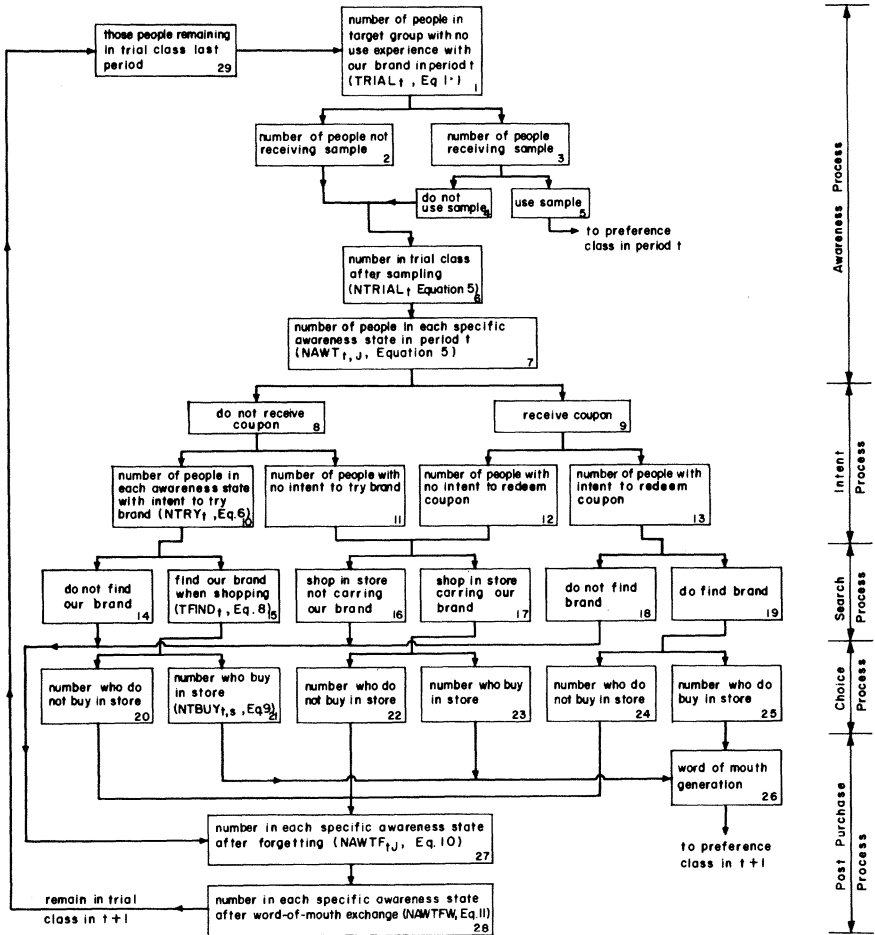


Fig. 2. Over-all potential-trial-class process-flow diagram: [Note: Equation numbers are given where mathematical equations are defined in the text; others are described verbally in the text. Box numbers are referred to in the text by { }.]

replicate this model with the flow diagrams and equations presented here. To facilitate this process, the boxes are numbered and references to these boxes will be by the number enclosed in braces { }.

Potential trial class (see Fig. 2). First, the number of people in the potential-trial class must be specified. Since the purchase-history classes

form a mutually exclusive and collectively exhaustive set, in the first period the number of people in the trial class is the current number in the target group for the product. In succeeding periods, it is the target groups less the number in the preference and loyalty classes; see box {1}. Then,

$$\begin{aligned} \text{TRIAL}_t = & \text{TGTGR}_t - \text{NPREF}_{t-1} \\ & - \text{NLOYL1}_{t-1} - \text{NLOYL2}_{t-1} - \text{NNLOYL}_{t-1}, \end{aligned} \quad (1)$$

where

$\text{TRIAL}_t$  = number of people in trial class in period  $t$ ,

$\text{TGTGR}_t$  = number of people in target group of the product in period  $t$ ,

$\text{NPREF}_{t-1}$  = number of people in preference class in period  $t-1$ ,

$\text{NLOYL1}_{t-1}$  = number of people in the loyalty I class in period  $t-1$ ,

$\text{NLOYL2}_{t-1}$  = number of people in the loyalty II class in period  $t-1$ ,

$\text{NNLOYL}_{t-1}$  = number of people in the nonloyalty class in period  $t-1$ .

The number of people in the target group for the product is forecast to be some reference level, but it can be influenced by advertising expenditures or by the total number of samples of the new product sent by all the firms in the industry. Then,

$$\begin{aligned} \text{TGTGR}_t = & \text{FTGTGR}_t \cdot \overline{\text{RADIND}}(\text{ADIND}_t/\text{FADIND}_t) \\ & + (\text{SMIND}_t - \text{FSMIND}_t) \\ & \cdot (1 - \text{FTGTGR}_t/\text{PWORLD}_t) \cdot \text{SAMPUS}, \end{aligned} \quad (2)$$

where

$\text{FTGTGR}_t$  = forecast reference number of people in the target group in period  $t$ ,

$\overline{\text{RADIND}}$  = advertising response function,

$\text{ADIND}_t$  = actual industry advertising expenditure in period  $t$ ,

$\text{FADIND}_t$  = forecast industry advertising expenditure in period  $t$ ,

$\text{SMIND}_t$  = total number of samples sent out by firms in the industry in period  $t$ ,

$\text{FSMIND}_t$  = forecast reference number of samples to be sent out by firms in the industry in period  $t$ ,

$\text{PWORLD}_t$  = potential number of people who could possibly be users of this product,

$\text{SAMPUS}$  = percent of people who receive samples who use them and are pleased with the product.

This equation describes the number in the industry as the forecast number times a response function that represents the effects of advertising levels different than forecast, plus the effects of samples when they are given in quantities other than expected. The advertising-response function represents the proportionate change in the number of people in the industry as the ratio of actual to expected industry advertising expenditure departs

from one. This allows a completely free format for defining the form of advertising response. The function will be defined by a large number of discrete entries. If a ratio does not fall on a discrete point, linear interpolation will be used. The sampling effect in equation (2) represents the fact that when someone not now in the direct target group receives a sample, uses it, and is pleased, he can be considered a prospective buyer. This part of the equation, therefore, states that the number of samples sent by all firms times the percent of people not now in the target group times the sample usage rate represents a best estimate of the number of new people added to the potential user group through sampling at other than the expected level.

The sampling effect is important in many truly new products, since it enables a person to experience trial without overcoming the perceived risk implied in undergoing the sequence of awareness, intent, search, and choice; *see* boxes {2, 3, 4, 5}. The effects of such sampling may increase the total market, as indicated in equation (2), but it also has the effect of giving some customers of our brand a pseudotrial, so the number of people in the trial class for our brand should be modified for this effect. The number in the trial class after our firm's sampling {6} is

$$NTRIAL_t = TRIAL_t - SMFIRM_t \cdot (TRIAL_t / PWORLD_t) \cdot SAMPUS, \quad (3)$$

where

- TRIAL<sub>t</sub> = number of people in the trial class before sampling,
- SMFIRM<sub>t</sub> = number of samples sent by our firm in period *t*,
- SAMPUS = percent of people who use the sample and experience a pseudotrial.

The people who experience a trial because of sampling are moved on to the preference model.

The awareness section of the trial class describes the effects of advertising in creating flows of people into awareness states. The number of newly aware people whose awareness was created by advertising is the number of people unaware in the trial model times the percent of people becoming aware at various advertising levels; *see* {7}. Thus,

$$DADAWT_t = (NTRIAL_t - TADAWT_{t-1}) \cdot \overline{RADAWT(ADFIRM_t / FADFRM_t)}, \quad (4)$$

where

- DADAWT<sub>t</sub> = number of people newly aware resulting from our advertising level (ADFIRM<sub>t</sub>) in period *t*,
- TADAWT<sub>t-1</sub> = number of people remaining aware at the end of the last period,
- $\overline{RADAWT}$  = response function representing the fraction of people

aware of our brand, ads, or appeals at our advertising expenditure level ( $ADFIRM_t$ ) compared to the reference level ( $FADFRM_t$ ).

All the people will not gain the same awareness on seeing an ad—some will be aware of specific appeals, while others will be aware only of seeing the ad and will have no specific recall. For example, specific awareness-state designations for a new soap may be 1 for unaware, 2 for ad-aware only, 3 for aware of cleaning power only, 4 for aware of gentleness appeal only, 5 for aware of gentleness and cleaning power. The number of people in each awareness state is the number remaining after the last period plus the new people made aware of some appeal times the percent of these who are made aware of a *specific* appeal; see {7}. Thus,

$$NAWT_{t,J} = NAWTFW_{t-1,J} + \overline{DADA}WT_t \cdot \overline{RADAPT}(ADFIRM_t/FADFRM_t) \quad (5)$$

$$\cdot \overline{RAPSPT}(ADFIRM_t/FADFRM_t, J),$$

where

$NAWT_{t,J}$  = number of people in appeal-awareness state  $J$ ,

$NAWTFW_{t-1,J}$  = number of people in appeal-awareness state  $J$  at the end of the last period after forgetting and word-of-mouth transfer [to be defined in equation (11)],

$\overline{RADAPT}$  = response function representing the proportion of people newly aware who become aware of *some* appeal at our advertising level  $ADFIRM_t$  relative to our reference level  $FADFRM_t$ ,

$\overline{RAPSPT}$  = response function representing percent of people who are aware of *some* appeal who become aware of *specific* appeal  $J$ .

The response functions  $\overline{RADAPT}$  and  $\overline{RAPSPT}$  are functions of advertising, because, as advertising expenditures are increased, the relative awareness-state compositions may change. The awareness states defined in the trial class include all people in the trial class, so the people aware of ads only (no specific content recall) is the difference between the total ad awareness and the sum of the specific appeal-awareness states. The population of brand-aware only is the difference between total awareness and ad awareness. The remainder of the people in the trial class are in the unaware state.

Awareness must now be translated into intent; see {10, 11}. The number with intent to try is the sum of the number with intent to try in each awareness state, where each state has its own intent rate, modified by the effects of competitive advertising. Thus,

$$\text{NTRY}_t = \sum_J \text{NAWT}_{t,J} \cdot \text{TRATE}_{t,J} \cdot \overline{\text{RACOMT}}[(\text{TCPTA}_t/\text{ADIND}_t)/(\text{FTCPA}_t/\text{FADIND}_t)], \quad (6)$$

where

$\text{NTRY}_t$  = number of people with intent to try in period  $t$ ,

$\text{TRATE}_{t,J}$  = percent of people in awareness state  $J$  who intend to try in month  $t$ , that is, show a predisposition to try,

$\overline{\text{RACOMT}}$  = response function describing the effects of total competitive advertising (defined as  $\text{TCPTA}_t$ ) as a percent of total industry advertising (i.e.,  $\text{ADIND}_t$ ) relative to the expected proportion of competitive advertising that is the reference competitive advertising  $\text{FTCPA}_t$  divided by the reference total industry advertising  $\text{FADIND}_t$ .

Note that the trial intent rate  $\text{TRATE}$  is time varying. This allows the trial proneness of the group currently in the trial class to vary over time. This is especially useful in describing the flow of innovators out of the trial class. As they move out over time, the trial intent will drop, reflecting that the remaining people are less trial prone. This gives the model the ability to consider the effects of innovators, even though they are not specifically defined as a different market segment.

A common new-product marketing tool is the use of coupons offering a price reduction. To encompass this marketing-mix element, the model breaks out those who receive a coupon and have intent to redeem it (see Fig. 2, {8, 9}).  $\text{NTRY}_t$ , therefore, does not include those who received a coupon and intend to take it to the store. These people are classified separately, {12, 13}, on the basis of the observed fraction who state a definite intent to redeem the coupon.

The people with intent now search for the product by shopping at their favored type of retail store (e.g., drug, food, variety). Their ability to find the product will depend upon the number of stores carrying the product, which, in turn, depends on our sales effort, the number of stores now stocking the product, and the middleman-margin trade promotion, or 'deal,' offered the retailer relative to competitive 'deals.' Consequently,

$$\begin{aligned} \text{AVAIL}_{t,s} = & \text{AVAIL}_{t-1,s} + \text{SLCAL}_{t,s} \\ & \cdot (1 - \text{AVAIL}_{t-1,s}/\text{NSTOR}_{t,s}) \\ & \cdot \overline{\text{RDEAL}}(\text{DEAL}/\text{ADEAL}) - \text{DROP}_{t,s}, \end{aligned} \quad (7)$$

where

$\text{AVAIL}_{t,s}$  = number of stores of type  $S$  that stock our product in period  $t$ ,

$\text{SLCAL}_{t,s}$  = number of sales calls on store type  $S$  in period  $t$ ,

$\text{NSTOR}_{t,s}$  = total number of stores of type  $S$  in period  $t$ ,

$\overline{\text{RDEAL}}$  = response function representing the percent of stores who

stock our product at a specific middleman deal (DEAL) relative to the average competitive deal (ADEAL),  
 $\text{DROP}_{t,s}$  = number of stores who drop our product when its sales are below their expectations,  
 $= \text{AVAIL}_{t-1,s} \cdot \overline{\text{RDROP}}(\text{RTHRU}_s/\text{FTHRU}_s)$ , where  $\overline{\text{RDROP}}$  is a response function representing the percent of stores who will drop our product when the average of the last two month's sales  $\text{RTHRU}_s$  is below expectation  $\text{FTHRU}_s$ . When  $\text{RTHRU}_s > \text{FTHRU}_s$ ,  $\overline{\text{RDROP}}$  reflects out-of-stock situations.

The drop term is added to reflect the shrinkage in distribution that occurs if the product sales growth is not satisfactory. When the percent of stores carrying the product is calculated, the number of people who have intent to try to find the product is the number who find the product at their favorite retailer plus the number who will look in another store for the product if it is not available in their favorite store; see {14, 15}. Thus,

$$\begin{aligned} \text{TFIND}_t = & \sum_s \text{PSHOP}_s \cdot \text{NTRY}_t \cdot \text{AVLPCT}_{t,s} \\ & + \sum_s \sum_{ss} \text{PSHOP}_s \cdot (1 - \text{AVLPCT}_{t,s}) \\ & \cdot \text{NTRY}_t \cdot \text{PSWST}_{s,ss} \cdot \text{AVLPCT}_{t,ss}, \end{aligned} \quad (8)$$

where

- $\text{TFIND}_t$  = number of people who have intent to try to find the product,
- $\text{PSHOP}_s$  = proportion of people who deem store  $S$  as their favored retailer for this type of product,
- $\text{AVLPCT}_{t,s}$  = percent of stores of type  $S$  carrying the product,  
 $= \text{AVAIL}_{t,s}/\text{NSTOR}_{t,s}$ ,
- $\text{PSWST}_{s,ss}$  = proportion of people who do not find the brand at their first-choice store who will switch to store  $SS$ .

A similar equation describes how many no-intent people or coupon holders are in a store with the brand; see {16, 17, 18, 19}.

The people who find the product and have intent now must make an in-store decision either to buy the product or not. At this point the consumer perceives the shelf price and must determine if the price relative to existing products is acceptable. This may be viewed as a weighing of the relative advantage of the new product versus the relative price and risks of trial. The risks of trial may be buying a product that does not work or may be more widely based social risks. These phenomena can be structured by stating that the percent of people who exercise their intent will depend upon the new-product price relative to the price standard for similar old products or the expected price of a completely new product. The

number actually purchasing {21} is

$$\text{NTBUY}_{t,s} = \overline{\text{TFIND}}_{t,s} \cdot \overline{\text{RPDIFT}}[(\text{PR}_{t,1} - \text{SPR}_t) / \text{SPR}_t] \cdot \overline{\text{RPOP}}(\text{SD}_t / \text{FSD}_t), \quad (9)$$

where  $\overline{\text{RPDIFT}}$  is a response function representing the percent of people who will exercise their intent when presented with our specific price  $\text{PR}_{t,1}$  relative to the price standard  $\text{SPR}_t$ .  $\overline{\text{RPOP}}$  is a response function representing the point-of-purchase effects of our special displays  $\text{SD}_t$  relative to the expected level of our display activity  $\text{FSD}_t$ . The people with a coupon perceive a lower shelf price and are described by an equation similar to (9) with the price equal to the shelf price less the coupon 'price off' amount; see {24, 25}.

In some cases, the price-response expression may not be needed because of the particular nature of a product; in such a case, it could be removed by setting its value to one for all prices. It is the judicious choice of functions and phenomena to be included or excluded that makes the behavioral-process model effective. As a further example, equation (9) implies people with no intent to try will not purchase. In some products, the in-store environment may actually create awareness and intent; in such a case, the number who try should be increased by the people with no intent who, when entering the store, are made aware, develop intent, and purchase the product because of the point-of-purchase display. Usually this will be a small effect, but in some product classes it may be justifiable to add more detail because of the behavioral process characterizing the product, and therefore this option is in the model; see {22, 23}.

The total number of triers is the sum of the triers in each store type. The people who purchase are moved from their awareness states on to the preference class on the assumption that the number who bought in an awareness class is proportional to the intent rate of that class. Those who remain experience forgetting {27}, and may receive or request word-of-mouth communication {28}. The number of people in a specific awareness state is the number remaining after purchase, less those who forget to lower awareness states plus those who forget to the state from higher awareness states. Thus,

$$\begin{aligned} \text{NAWTF}_{t,J} = & \text{NAWTA}_{t,J} + \sum_{K>J} \text{NAWTA}_{t,K} \cdot \text{RFRGT}_{K,J} \\ & - \sum_{K<J} \text{NAWTA}_{t,J} \cdot \text{RFRGT}_{J,K}, \end{aligned} \quad (10)$$

where

$\text{NAWTF}_{t,J}$  = number of people in awareness state  $J$  after forgetting in the trial class,

NAWTA<sub>t,J</sub> = number of people in awareness state *J* after trial purchasers have been moved to the preference class,

RFRGT<sub>J,K</sub> = percent of people who forget from awareness state *J* to awareness state *K* in the trial class,

RFRGT<sub>K,J</sub> = percent of people who forget from state *K* to awareness state *J* in trial class.

The trial-class section of the word-of-mouth process {26} is conceptualized by two mechanisms: (1) buyers initiate word-of-mouth about appeal *J*, or (2) nonbuyers request information about appeal *J*. The total amount of word-of-mouth for all classes is the sum of the buyer-initiated word-of-mouth and the nonbuyer requests for word-of-mouth communication that reach someone with some awareness about the appeal. This pool of word-of-mouth information is assumed to fall randomly upon the populations of the awareness states. The amount received by a state is proportional to its size compared to the total target group. If they receive information about a higher awareness state, they move to that state. If they receive information they already possess, they remain in the same state. The awareness-state population after word-of-mouth is therefore the original value plus those who have moved to the state from lower awareness states less those who have moved to higher states {28}. The number of people is

$$NAWTFW_{t,J} = NAWTF_{t,J} - \sum_{K>J} WOM_{t,K} \cdot (NAWTF_{t,J} / TGTGR_t) + \sum_{K<J} WOM_{t,J} \cdot (NAWTF_{t,K} / TGTGR_t), \tag{11}$$

where

WOM<sub>t,K</sub> = total number of word-of-mouth exchanges about appeal *K* in the pool,

TGTGR<sub>t</sub> = total number of people in the target group in period *t*.

This number of people in each awareness state is an input to the next period [see equation (5) and {29}].

*Preference class* (see Fig. 3). In order to be placed in the preference class by definition of the model, the consumer must have tried the product. He can leave the class by repurchasing and can remain in it only by not repurchasing our brand (see Fig. 1). The aggregate number in the preference class is the number in the class last period less those who purchased in the preference class last period {33} plus those who tried last period {32} plus those who used a sample this period {31}. Since all the people in the preference class have used the product, they will not be completely unaware of the product, and most will be aware of some specific characteristic as a result of using it. Some will not like the brand, while others will have a very positive experience, and still others may be aware of some characteristics of the brand but have not formed a definite opinion. Therefore,

it is meaningful on the basis of trial-use experience to again classify people by their awareness to specific product and advertising appeals with the understanding that one appeal state will represent negative- and one positive-use experience. The negative awareness state will accumulate those who dislike our brand and will buy competitive brands regularly. There

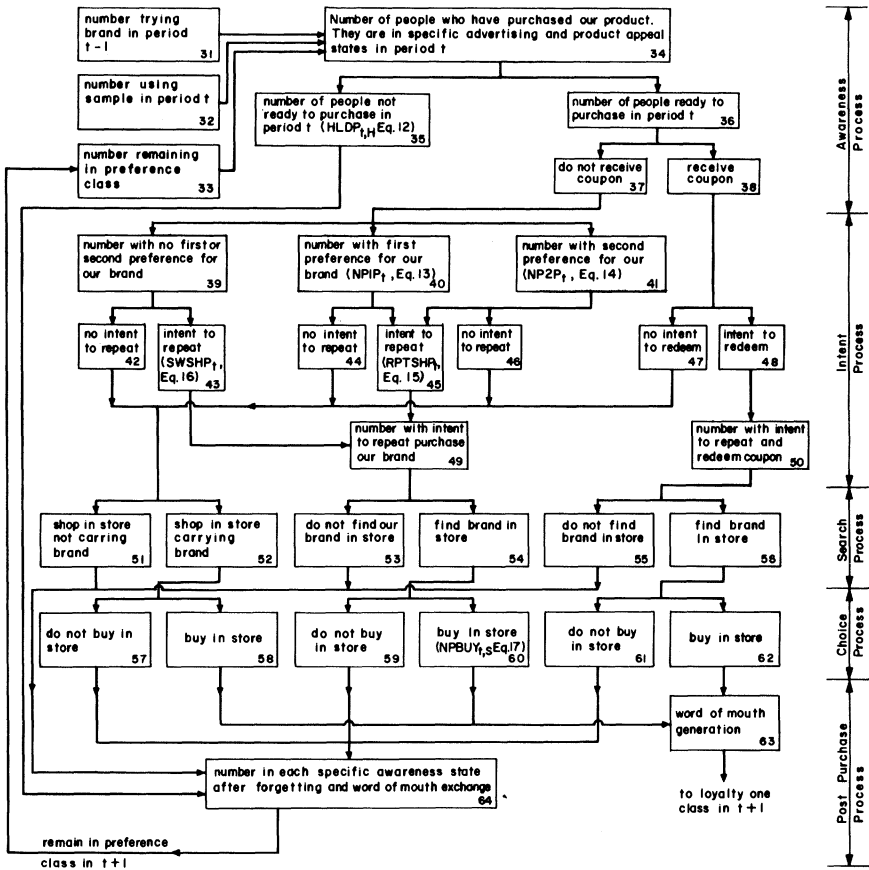


Fig. 3. Over-all preference-class process-flow diagram.

is a zero or low probability of purchase of our brand from the negative state. Although the trial-product use is the prime determinant of a person's awareness, advertising can still play an important role in products where the appeals are sociologically or psychologically based. Here advertising is needed to reinforce awareness to these utilities. Even positive use may be reinforced, since advertising plays a role in reducing cognitive dissonance. Therefore, the new awareness of the product and numbers in each awareness

state are functional on advertising although this function should be less responsive than the corresponding functions in the trial-class process. Equations similar to (4) and (5) parameterized for the preference class are used to define the awareness states {34}.

All people in the preference class may not have the need to repurchase in the next period, since consumers use the product at varying rates. These different purchase frequencies are included in the model by defining holding states that contain the number of people who will be ready to purchase in  $H$  periods:

$$HLDP_{t,H} = HLDP_{t-1,H+1} + [TBUY_{t-1} + SMFIRM_t \cdot SAMPUS(NTRIAL_t/PWORLD_t)] \cdot FREPR_H, \tag{12}$$

where

$HLDP_{t,H}$  = number of people who will be ready to purchase in  $H$  periods,  $H = 1, \dots, h$ ,

$FREPR_H$  = frequency of purchase defined by the percent of consumers repeat purchasing every  $H + 1$  months.

This equation reflects the fact that all consumers do not buy each period. The distribution of purchase rates is used to place people in holding states as they enter the preference model by a trial  $TBUY_{t-1}$ , or by sampling. The number in the preference model less the number of people in some holding state {35} is the number of people who are ready to purchase in period  $t$  {36}.

For those ready to purchase, awareness must now be translated into intent or predisposition to repurchase. Those who receive a coupon are separated {37, 38} and classified on their stated intent to redeem the coupon {47, 48, 50}.

The others are processed by an awareness to preference and preference-to-intent process. The percent of people in each awareness state with first preference will vary between states and the total number with first preference is the sum of the number with first preference in each awareness state {40}. Thus,

$$NP1P_t = \sum_J NAWP_{t,J} \cdot PIRATE_{t,J}, \tag{13}$$

where

$NP1P_t$  = number with a first preference for brand,

$PIRATE_{t,J}$  = percent of people in awareness state  $J$  who have a first preference for the product,

$NAWP_{t,J}$  = number aware of appeal  $J$  in period  $t$  in preference class and ready to buy.

Similarly, the number with a second preference for the brand {41} is

$$NP2P_t = \sum_J NAWP_{t,J} \cdot P2RATE_{t,J}, \tag{14}$$

where

P2RATE<sub>*t,J*</sub> = percent of people in awareness state *J* who have a second preference for the product.

The remaining people have no preference {39}.

The number of these people who convert their preference into intent will probably be less than 100 percent and will be influenced by competitive advertising efforts. Although the product-use experience was successful and adequately reinforced by our advertising, competitors may cause consumers to buy their product rather than ours through their relative advertising pressure. The number of people in the preference model who intend to repeat purchase {45} and who will purchase some product in period *t* is

$$RPTSHP_t = (NP1P_t \cdot BRP1P + NP2P_t \cdot BRP2P) \cdot \overline{AREL}[(ADFIRM_t/TCPTA_t)/(FADFRM_t/FTCPTA_t)], \tag{15}$$

where

BRP1P = percent of people with first preference who are expected to convert that preference into intent to repurchase,

BRP2P = percent of people with second preference who are expected to convert that preference into intent to repurchase,

$\overline{AREL}$  = response function representing the effects of competitive advertising by the proportionate reduction in the number intending to repurchase at our level of advertising ADFIRM<sub>*t*</sub> relative to total competitive advertising TCPTA<sub>*t*</sub> compared to the forecast ratio FADFRM<sub>*t*</sub>/FTCPTA<sub>*t*</sub>.

The development of intent to buy our brand in the preference model may come about not only from a preference for our brand. Some people may intend to buy our brand by switching from their preferred brand. Although this may not be a large number of people, it is significant in understanding the brand switching that takes place after trial, especially since competitive advertising affects the rate of switching. The number of switchers with intent to buy our brand {43} is

$$SWSHP_t = (NPREF_t - NP1P_t - NP2P_t) \cdot SWRFK \cdot \overline{ARELK}[(TCPTA_t/ADIND_t)/(FTCPTA_t/FADIND_t)], \tag{16}$$

where

NPREF<sub>*t*</sub> = number of people in preference class ready to buy in period *t*, but with no intent to redeem a coupon,

SWRFK = percent of people with no preference for our brand who develop an intent to buy our brand at reference competitive advertising,

$\overline{ARELK}$  = response function reflecting proportionate change in switch-

ing rate as total competitive advertising  $TCPTA_t$  as a percent of industry  $ADIND_t$  varies from the predicted reference ratio  $FTCPTA_t/FADIND_t$ .

The total number of people intending to repurchase our brand is the sum of the repeaters and switchers  $NPSHP_t$  {49} plus those with a coupon and an intent to redeem it {50}.

The preference-class consumers who have intent now search for the brand. Since they tried the product before entering this class, if they return to the same store they will find the product, unless the retailer has dropped it {53, 54}. The expression for the number who find the product is similar to equation (8), except that it applies only to those who do not return to the same store or whose regular store has dropped the product. The result is the number of people with intent who find the product at a particular store. Similar equations are used to define the number of people with coupons {55, 56} and the number of people with no intent {51, 52} in a store with the product.

Once in the store, the preference-model buyer is influenced by the in-store price and display. The proportion who carry out their intent and purchase is presumed to depend upon the relative perceived in-store effectiveness of each brand. In-store displays, facings, and price may also induce people with no intent for repurchase to buy our brand. The number of actual purchases in the preference model by those with intent and no coupon {60} is

$$NPBUY_{t,s} = TSHOP_{t,s} \cdot K \cdot \left[ \frac{(\text{PR}_{t,1,s}^{\text{SPRiS}} \text{FA}_{t,1,s}^{\text{SFAiS}} \text{SD}_{t,1,s}^{\text{SSDiS}} / \sum_i \text{PR}_{t,i,s}^{\text{SPRiS}} \text{FA}_{t,i,s}^{\text{SFAiS}} \text{SD}_{t,i,s}^{\text{SSDiS}})^{\text{EI}}}{1} \right], \tag{17}$$

where

$TSHOP_{t,s}$  = number of people entering store of type  $S$  carrying our brand with intent to purchase our brand (but with no coupon),

$\text{PR}_{t,i,s}$  = price of brand of firm  $i$  in store  $S$  in period  $t$ ,

$\text{FA}_{t,i,s}$  = number of package facings exposed on the shelf of brand of firm  $i$  in store  $S$  in period  $t$ ,

$\text{SD}_{t,i,s}$  = percent of stores of type  $S$  that have special displays for firm  $i$ 's brand in period  $t$ ,

$K$  = scale constant,

$\text{SPRiS}$  = sensitivity of price for firm  $i$ 's brand in store  $S$ ,

$\text{SFAiS}$  = sensitivity of facings for firm  $i$ 's brand in store  $S$ ,

$\text{SSDiS}$  = sensitivity of special displays for firm  $i$ 's brand in store  $S$ ,

$\text{EI}$  = elasticity of in-store environment for consumers with intent to buy our brand.

An equation similar to (17) with a different elasticity defines the number

of preference-model consumers with no intent in a store carrying our product, but who buy our brand {58}. This form is also used to describe the behavior of people with a coupon (and therefore a lower price) in the store {62}.

The number of facings is determined by the effectiveness of our brand relative to the middleman's expectations. If the retailer finds sales much higher than expected, he will allocate additional shelf facings to our brand. In this way, the in-store environment is affected by a combination of our controllable variables and the retailer's decision rules.

The total number of people who buy our brand is the sum of the buyers in each store. These buyers exit to the loyalty I model. The remaining nonpurchasers undergo forgetting and word of mouth {64} by the same process as trial buyers. The process is described by equations (10) and (11) when these equations are parameterized for preference rather than trial buyers.

*Loyalty classes* (see Fig. 4). In the loyalty classes the level of detail in considering the behavioral process is lower than in the preference or trial classes, because in these classes it is assumed that consumers have a positive attitude towards the brand and have established a source of supply. The number in the loyalty I class are those who were in the class last period {67} plus those who repurchased in the preference class {66} less those who purchased competitive brands or our brand in the loyalty I class plus those who purchased our brand in the nonloyalty class {65}. See Fig. 1.

The number of people intending to buy our brand this period is the number who have a purchase opportunity {70} this period times the repeat rate for loyal buyers less the effects of competitive advertising in winning over part of our loyal buyers {71, 72}. Assuming the loyal buyer has a source of supply for our brand, the number who actually purchase is the number with intent decreased by in-store effects. In this model it is presumed that facings and displays are not important, but that relative price changes could cause our loyal buyers to switch to other brands. For example, a large price-off deal by a competitor could decrease our rate of repurchase. The number of loyalty I buyers {73} is

$$\begin{aligned}
 \text{BUYL}_t = & (\text{NLOYL}_t - \sum_n \text{HLDL}_n) \cdot \text{REPT1} \\
 & \cdot \overline{\text{AREL1}}[\text{ADFIRM}_t / (\text{ADIND}_t / \text{QFIRM}_t)] \\
 & \cdot \overline{\text{PREL1}}[\text{PR}_{t,1} / (\sum_i \text{PR}_{t,i} / \text{QFIRM}_t)],
 \end{aligned}
 \tag{18}$$

where

- REPT1 = percent of loyalty I consumers who intend to repeat purchase our brand at reference price and advertising levels,
- NLOYL<sub>t</sub> = number of people in loyalty I class in period *t*,

$HLDL1_H$  = number of people who will be ready to purchase in  $H$  periods  
 [see equation (12) for analogous calculation],

$AREL1$  = response function representing the effects of our advertising  
 $ADFIRM_t$  relative to the average level of advertising per

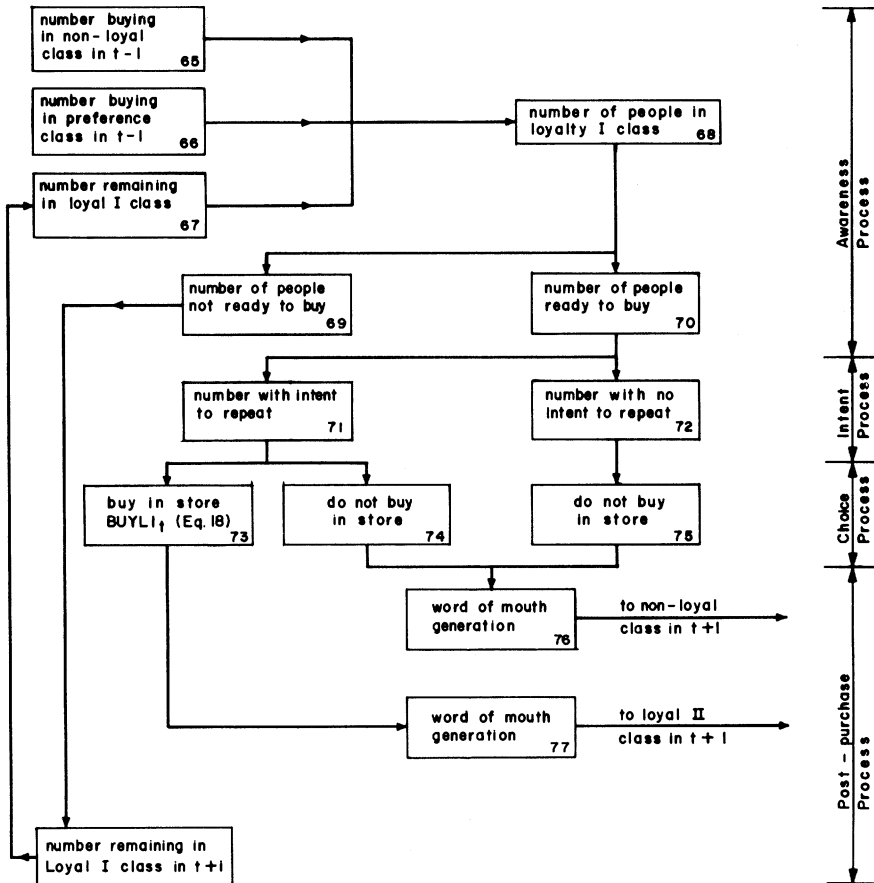


Fig. 4. Over-all loyalty process-flow diagram.

firm  $ADIND_t/QFIRM_t$ , where  $QFIRM_t$  = number of firms in industry in period  $t$ , by the proportionate reduction in the intent rate in the loyalty I model,

$PREL1$  = response function representing the effects of our price  $PR_{t,1}$  relative to the average price by the proportionate reduction in our repeater loyalty I model buyers in the store.

The buyers of our brand in this class proceed on to the loyalty II class,

while buyers of competitive brands go to the nonloyal class. The loyalty buyers of our brand can generate word-of-mouth which is added to the total pool of word-of-mouth. Loyalty I buyers are all assumed to be aware of some positive product features because of two purchases of our brand, so those remaining in the model are not subject to forgetting; rather they are considered to retain awareness to at least one positive appeal.

The loyalty II class is structured in the same way as loyalty I. The number of people in the class is the number who were in the class last period plus those who purchased in loyalty I last period less those who purchased a competitive brand last period in the loyalty II class. In the loyalty II class it can be expected that the repeat rate will be higher and the response functions will be less sensitive than in the loyalty I class. The nonloyal class contains the people who did not repeat in loyalty I or II. It is similar to equation (18) with different response functions and lower repeat rates.

*Cost, profit, and risk submodels.* After the total number of buyers has been determined, the total revenue and total cost can be determined by usual accounting methods and by the application of an appropriate cost function. The profit attributable to the brand, however, may not be the difference between these revenues and costs. If the examination of consumer panel purchase sequences indicates the new product is interdependent with other brands offered by the firm, the loss or gain in profits of the other brands should be considered to calculate differential profits (*see* Urban<sup>[38]</sup>). The differential profit can be obtained by subtracting the profit that would have been earned by the existing product if consumers had not tried or repeat purchased the new product instead of the old product. Conversely, if the new product is complementary to existing products, the additional profit earned by old products because of consumers buying the new product should be added to the new product's accounting profit to determine differential profits. The present value of the differential-cash-flow profits reflects in one figure the expected improvement in the company's position resulting from introducing the product.

The risk associated with the brand can be determined by describing distributions about the input parameters and running a large Monte Carlo analysis to determine the distribution about total differential profits or by describing a subjective distribution about expected sales and translating it into a differential profit distribution. This Monte Carlo analysis need not be run for each policy alternative; rather it can be done only once after the final introductory strategy has been found. The risk-return-investment balancing can be made by examining the probability of achieving a target rate of return, as suggested by Urban,<sup>[38]</sup> or target payback as suggested by Charnes et al.<sup>[9]</sup> If an appropriate criterion is set, the model will recom-

mend a GO, ON, or NO decision for the brand, given a particular introduction strategy: that is, if the probability of achieving the target rate of return is greater than the GO level, a GO decision is made; if the probability is less than the GO level, but above the NO level, an ON decision is made and more information is collected, or efforts are directed to improving the product; if the probability of achieving the target rate of return is less than the NO level, the product is rejected.

If the ON decision is indicated, selecting the best study to carry out is difficult, since not only are there a number of complex market-research alternatives for the next study, but there is an information network of studies to consider. A good selection procedure looks down the network in deciding on the next best step. The basic approach to this problem is via Bayesian value of information, but it is outside the scope of this paper to discuss this problem. For a review of this problem relative to new products, see Urban.<sup>[40]</sup>

### ***Finding the 'Best' Strategy***

The model just described is designed to yield recommendations about the introductory strategy for the product and aid adaptive planning during national introduction. The model must specify what values *should* be set for the controllable variables of price, advertising expenditures, middleman deal, number of sales calls, and number of samples. These variables have been directly linked to the behavioral diffusion process in the equations so that alternatives can be evaluated. The design criteria were to build a model that could be searched efficiently for the best strategy alternative, but still retain the behavioral richness of the consumption process. In establishing the level of detail necessary to accomplish the first objective, compromises had to be made. In almost all sections of the model more detail could be justified by a more microlevel consideration of the process. For example, a number of market subsegments that follow different decision processes could be specified. The number of segments would increase the computer run times for the model, so the additional detail would have to be traded off against more computer expense in evaluating alternatives and collecting additional data. Similarly, there is an option in the model to divide retailers into those directly serviced and those indirectly serviced by wholesalers if the particular product could justify such additional detail. The detail in each of the classes was judiciously chosen to ensure the ability to search for best solutions with a reasonable expenditure of funds. The model is felt to be at an efficient and sufficient level of detail and flexibility, but certain frequently purchased consumer goods may require additional depth because of behavioral peculiarities associated with them.

In order to find the best, or a good, strategy for this model, iterative

techniques must be utilized, since the more analytical and algorithmic techniques are not applicable to a nonlinear, discontinuous, dynamic model such as this one. In reviewing iterative techniques, a number of mechanical heuristics are available (*see* WILDE AND BEIGHTER<sup>[42]</sup>). In the introduction of a new product, however, there is a potential heuristic in the brand or new-product manager. He has lived with the brand's development and the product market and is a valuable subjective source of reasonable strategies. This man heuristic can be tapped through a simple on-line program that asks him to specify initial values, ranges, and increments within the range for each variable (*see* Urban<sup>[39]</sup>). These values are run in all combinations and the best results are reported back to the manager. He then can specify new values, ranges, and increments for evaluation. In this way the man uses his 'good business judgments' to guide the search to good and sometimes best solutions in a reasonable number of steps. Experience with this behavioral-process macromodel indicates that about ten alternatives can be evaluated in one minute on a IBM 7094 computer, so that, with a reasonable expenditure of funds (say less than \$1,000), a good, or perhaps best, strategy can be found.

In searching strategy alternatives, the model has the capability of accepting alternate adaptive rules for competitors. For example, competitors can be given the strategy of following our advertising changes or reacting to our market-share improvements. It is also useful to generate profit payoffs for the product under these alternative competitive environments, since the payoff matrix can be analyzed by game theory or Bayesian means to find the best strategy, given possible competitive strategies.

It is at the best strategy that the product should be evaluated. Then it can be assured that a good product will not be rejected because of a poor strategy decision. At this point, the tasks for the model are to predict sales and profits for the new product, identify the profit-maximizing strategy for it, and recommend a GO, ON, or NO decision for it.

### ***The Model and Adaptive Control in National Introduction***

If the product receives a GO decision, its national introduction is initiated. During national introduction, the behavioral-process macromodel serves an important function in diagnosing problems in national introduction, generating updated sales forecasts, and recommending solutions to the problems. The national introduction can be plagued with problems from at least four sources. First, consumers are fickle and their behavioral responses (e.g., preferences, intents, or awareness rates) may change from the test levels by the time the product reaches the national market. Second, competitors may change their strategies upon national introduction. Third, the test-market cities may not have accurately measured the market phenomena. Fourth, there may be a failure in the execution of the national

plans by the firm (e.g., distribution goals not obtained by the sales force.) These sources of change can produce undesirable or desirable sales trends; for example, preference rates may shift away from the product or towards it. Since a number of errors can occur simultaneously, observing only sales or market shares could mask many problems. The behavioral-process model enables decision makers to monitor microlevel consumer-process elements (e.g., recall, intent) and determine if these behavioral responses are different from those observed in the test. Errors in executing the firm's plans can be observed in the levels of the controllable variables and their results (e.g., availability and awareness levels). Competitors' changes can be monitored in changes in the level of their controllable variables. If any changes occur in the controllable variables or in the behavioral responses, the model should be run with the updated values to see if these values accurately predict the current sales level. If they do, one can be reasonably certain that the behavioral changes identify the problem. This microlevel approach to problem finding is different from observing only the market share or sales level and assuming no problems exist if it is satisfactory. The superficial consideration of problem identification can lead to a failure to identify basic consumer response problems that may lead to substantially different results in the future.

The behavioral-process macromodel supported by an adequate data bank can diagnose problems in the national introduction based on early sales and behavioral data. After the changes in response or variation of the controllable variables have been found, the model parameters and response functions should be updated and conditional forecasts generated. This is an adaptive use of the behavioral-process macromodel. There are a number of problems in updating this type of complex model. First, it is a multivariate model, so Bayesian posterior analysis will be complex (*see* LITTLE<sup>[20]</sup> for the Bayesian approach to a simpler model). Secondly, the model is a multiperiod model, and updating must be not only for the next period, but also for other future time periods. This limits many updating schemes, since discrete adjustment of all future-period values of the parameters may not be realistic. For example, if the competitor increases his advertising in period  $n$ , it would not be wise to update all the values for the future periods if it were known that this was a short-run strategy change. Similar situations may occur in basic response functions when known short-run phenomena occur. The updating of this model will therefore require substantial managerial input. This subjective judgment is not as attractive as an analytic procedure, but it must be recalled that the model is designed to be a tool for managers, so this high level of interaction is useful in gaining implementation and will utilize the manager's experience in the market.

Although the updating of multiperiod parameters will require mana-

gerial judgments, some existing procedures can be used to carry out some kinds of updating. For example, new national-sample data can be integrated with old test-market sample data by Bayesian procedures for parameters such as the first repeat rate [REPT1, equation (18)]. This kind of updating is particularly convenient if a Beta distribution fits the prior distribution of the behavioral response rates (*see* MORRIS<sup>[24]</sup> for this procedure). Another simple approach is to smooth the new parameter estimate with the old estimate by an appropriate smoothing constant. Finally, a national parameter can be discretely changed to the observed value if at the new value the firm realizes it had made a mistake in measuring or interpreting the test data.

The method of updating should reflect the diagnosis of the problem. Simple methods can be used if new information about a parameter is obtained, but no drastic environmental change has taken place. If a basic change has been diagnosed, then the manager-model interaction should be used to establish the updated set of parameters for the future periods.

After the appropriate updating has been carried out, a revised forecast can be generated. But this is not the end of the model's usefulness. The revised model parameters can be searched to find the best response to the changes. For example, if trial rates are higher than expected, but repeat rates are lower, what is the best level for advertising? This question can be answered by searching the model on the basis of the revised parameters to find the most profitable revised national strategy. Given the new definition of a strategy, procedures to collect additional information by observation or experimentation should be instituted so the firm can adapt to future changes in the market environment. The use of the model as an adaptive mechanism gives it a potential not only to improve the go national decision process, but also the national introduction itself.

#### DATA BANK

THE BEHAVIORAL-PROCESS model outlined in the previous section requires a large amount of input. This input is at the behavioral-process level and must be drawn from a substantial data base. This section outlines the data base needed to support this frequently-purchased-new-product analysis.

The data base available for the go national decision of a new consumer product is the information that can be collected during its test marketing. Usually the brand is marketed in a number of cities and, if adequate information-gathering procedures are instituted, the input demands of the model can be satisfied. The following types of data-collection instruments are needed: (1) store-audit data, (2) special awareness surveys, (3) consumer-panel data, (4) salesmen's call reports, (5) audits of advertising

TABLE I  
DATA-BANK AND STATISTICAL-BANK INPUT REQUIREMENTS

Model input <sup>(a)</sup>	Data-bank requirement	Statistical-bank requirement
<u>RADIND</u> (2) <sup>(b)</sup> <u>RPDIFT</u> (9) <u>RPOP</u> (9) <u>SPRiS</u> (17) <u>SFAiS</u> (17) <u>SSDiS</u> (17) <u>EI</u> (17) <u>FTGTGR</u> (2) <u>RDROP</u> (7)	Audit of stores in test-market cities	Regression General classification and analysis program Nonlinear numeric estimation
<u>TRATE</u> (6) <u>FREPR</u> (12) <u>SWRFK</u> (16) <u>REPT<sub>1</sub></u> (18) <u>AREL<sub>1</sub></u> (18) <u>PREL<sub>1</sub></u> (18) <u>FTGTGR</u> (2) <u>SAMPUS</u> (2, 3)	Consumer-purchase-history panel in the test cities	General classification and analysis program
<u>RADAWT</u> (4) <u>RADAPT</u> , <u>RAPSPT</u> (5) <u>RACOMT</u> (6) <u>RFRGT</u> (10) <u>P<sub>1</sub>RATE</u> (13) <u>P<sub>2</sub>RATE</u> (14) <u>AREL</u> (15) <u>ARFLK</u> (16) <u>WOM</u> (11) <u>SAMPUS</u> (2, 3) <u>PSHOP</u> (8) <u>PSWST</u> (8) <u>BRP<sub>1</sub>P</u> , <u>BRP<sub>2</sub>P</u> (15)	Special awareness, preference, intent, usage and word-of-mouth questionnaires Call-back questionnaires	Regression General classification and analysis program
<u>RDEAL</u> (7)	Salesmen's call reports	Classification analysis
<u>ADIND</u> (2, 6, 18) <u>TCPTA</u> (6, 15, 16)	Audits of test-city media	
Advertising and production costs	Accounting data	Classification

<sup>(a)</sup> This list only includes parameters given in the text equations, but other parameters are dealt with in an analogous manner.

<sup>(b)</sup> Equation numbers are in parentheses.

media, and (6) the firm's internal records. See Table I for some of the input usage of these data.

### ***Store-Audit Data***

The store audits should be a representative sample of the stores in the test cities. This will allow retail sales levels and market shares (if competitive products exist) to be determined. The audits should monitor sales, inventory, price, shelf facings, special displays, and out-of-stock conditions for the brand and its competitors in all types of stores. These data are useful for estimating the effects of our changes in suggested price, margins, or use of price-off deals. By examining these data on a disaggregated basis, it will be found that similar types of stores present different in-store environments (e.g., different prices, numbers of facings, special displays). These historical differences may supply the basis for estimating the sensitivity of sales to different prices or special displays.

The retail sales levels in the different cities are also useful in determining the effects of alternate advertising levels that may exist between cities and over time. It would be desirable to have the differences result from controlled experiments, as outlined by BANKS<sup>[2]</sup>; this should be done unless budget restrictions preclude such expenditures. The value of experimental data over observational data can be assessed by examining the confidence distributions about the parameters as reflected in the risk of the product (i.e., standard deviations of the differential profit distribution), and the sensitivities of the expected profits to the parameters' values. If the profit is very sensitive to a parameter, resources should be devoted to setting up controlled experiments.

If observational data are relied upon, the risk of the project will be higher, and an ON decision (collect better information) will result if this risk level precludes a GO decision. Although it is tempting to specify a data base that reduces the risk to almost zero, a more mature managerial approach is to specify a sufficient data base and only carry out extensive experimental studies if an ON decision is reached and a sensitivity analysis and Bayesian value-of-information analysis indicate the information would be worthwhile to collect.

### ***Special Questionnaires***

Special questionnaires are useful in obtaining awareness and intents of consumers in the test cities. These should be administered each period to record the specific recall people have to advertising appeals, the word-of-mouth they receive and its content, their preferences for the brands in the product class, their usage experiences, their intent to repeat or try, and their shopping habits. These data can be the basis for estimating aware-

ness levels and the composition of specific appeal classes. If advertising varies it can be used to estimate the awareness response to advertising expenditures. The longitudinal awareness levels obtained from such data can be useful in estimating forgetting rates. The preference and intent data will be basic to estimating preference rates and the transformations to intents. If competitive advertising pressures vary, these effects can be observed in the intent and usage rates. Finally, shopping habits are needed to estimate the consumer's favored retailer, so that distribution effects can be linked to preference and intent. Some of the questionnaires should be directed at finding out if people carry out their intent by recontacting some of the original respondents at a later time. Special surveys are also useful in assessing interdependencies between brands when the procedures of multidimensional scaling are used, as suggested by STEFFLRE.<sup>[37]</sup>

### ***Panel Data***

The panel of consumers in the test cities should be established and they should record at least the time of purchase, price, place of purchase, and receipt and use of samples. These data are a source for estimating the trial rates in each period, the frequency of purchase, the repeat rates, and brand-switching rates. They can also be used to assess the effects of changing advertising levels on repeat rates if advertising varies over time or between cities. Finally, they can be used in estimating the effects of samples in simulating trial experiences. They can also be useful in establishing a continuing panel to record awareness to ads and appeals to estimate forgetting rates.

### ***Salesmen's Call Reports***

Salesmen's call reports supply the basis for estimating the success rate in stocking the product at retail and the ability of salesmen to improve the in-store display of the product.

### ***Media Audits***

Audits of media in the test cities are needed to determine the extent of competitive advertising and serve as a check on planned advertising expenditures by our firm.

### ***Internal Records***

Internal company records supply data on the advertising expenditures of the firm and shipments of the product, along with other data on planned strategies and the basis for past decisions.

### ***Other Data Needs***

Test-marketing data are necessary for the go national decision, but samples of the same type of data should be collected nationally if the product is introduced, since the model is to be used adaptively during national introduction.

These six items of data are necessary to support the model. They have been described only in general terms, but a number of market-research firms offer such data-collection services; however, a full discussion of such market-research methods is beyond the scope of this paper. The point should be stressed that data at the behavioral-process level can be collected, and that they are the basis for determining the model inputs. It is reasonable to estimate the costs of collecting such information at about \$50,000–\$75,000, but all this is not incremental expense for the system, since some firms collect some or most of this information under current procedures.

### **STATISTICAL BANK**

THE BURDEN OF converting the raw data-base information into model inputs is the task of the statistical bank. This bank contains a collection of multivariate statistical routines capable of exhausting the information from a data base. To support the behavioral-process macromodel presented in this paper, the statistical bank must contain at least the following programs: (1) a multivariate regression, (2) a general conditional classification and analysis program, and (3) a nonlinear estimation program. The appropriate uses of these programs are presented in Table I along with the data to be analyzed and the input to be produced.

Linear regression can be used in estimating the effects of in-store relative price effects in trial (RPDIFT) by regressing the price difference between the new product and its chief competitor's shelf price against the market share (or sales) the new product achieves in the first periods of introduction in similar size and types of stores. Lagged regressions can be used to examine the effects of total advertising by all the products (RADIND) by a log-linear regression to total product-group sales over time with an appropriate carry-over term.

In analyzing the results from special awareness, preference, and usage questionnaires, it is useful to have a free-format program that can examine certain classifications of the data and calculate summary statistics based upon them. An on-line program called *Datanal*<sup>[23]</sup> has been developed at MIT to carry out this function. It allows sections of a data base to be abstracted, analyzed, and cross tabulated with other sections of the data base. For example, such a program could be used to analyze the special

questionnaires described in the data-bank section. It could separate the number of people who have used our product once and determine the specific awareness to ads or product appeals. These appeal classes could be further analyzed to see how many of each class have a first preference for our brand. Then the number with first or second preference could be tabulated against their intent with respect to future purchases. This capability is not only efficient, but it allows the researcher to pursue each newly found insight to exploit the information in the data base fully. This type of program can also be used to analyze consumer-panel records to estimate the trial-and-repeat rates necessary in the model.

The final program in the statistical bank is a nonlinear estimation program. This can be an iterative-search routine that will minimize the variation between a set of observed data and a set of model-generated data. The program can be best run as an on-line search, where a market researcher specifies the initial values of the parameters and a set of increments to be evaluated (*see Urban*<sup>[39]</sup>). This type of program can be used to estimate the sensitivities of price, facings, and special displays by minimizing the variation between observed sales in a store and the sales predicted by equation (17).

Other statistical routines that are included in usual computer program libraries may also be useful in interpreting the data. In general, the data base should be exhaustively analyzed so that all the insights it contains can be learned. For example, simple regressions of advertising to awareness and awareness to trial are useful to conduct. After all the statistical analysis is complete, the management scientist and manager face the task of reviewing the estimates and generating the best set of inputs. The manager must review the data because the theoretical assumptions of all the statistical routines may not have been satisfied, the standard errors of the estimator may be large, or because alternate statistical techniques may yield different results. In addition, the statistical programs only yield information about the statistical sampling error, and he must interpret the data-collection and measurement-instrument bias. Finally, some of the inputs may not be reflected in the data. For example, perhaps no data were available to evaluate the effects of alternate middleman deals on distribution. In this case, he will have to make his best estimate of the response. He can, however, specify confidence intervals about his estimates and examine the sensitivity of the decision to the inputs by running the model for alternate values.

The manager will remain a key element in the generation of input for new products because of the very complex multivariate and dynamic environment being analyzed and the rich base of prior knowledge the manager has accrued over his years of experience. An advantage of the

behavioral-process model is that it is structured in the way the manager visualizes the market. Successful marketing managers understand the behavioral processes of the market. Their experience can be linked to the process elements to gain the benefits of their good business judgment. In fact, the model's formal statement of the market processes usually leads to refinement of the manager's implicit model of the market and learning over time about the market mechanism.

### INPUT-OUTPUT CAPABILITY

THE MANAGER should be able to communicate easily with the new product-analysis system. He should be able to determine the sensitivities of the model to inputs, to explore the full implications of alternate strategies, and to search for best strategies. This easy communication is best achieved by a conversational on-line program that allows the manager to direct the computer model. To this end, the behavioral-process macromodel described in this paper has been placed on line in a program (*see* the Appendix for a typical on-line session). The on-line program associated with SPRINTER Mod III allows the manager to access and display any of 300 of the model's inputs or calculated values by typing the command DISPLAY and an appropriate key number. He can display all data pertaining to the item or specific portions of vectors or matrices. In addition to the display capability, the manager can update any values from the console. The UPDATE command enables the managers to change input variables or parameters easily, and by re-running the model they can learn the sensitivities of the outputs to their changes.

A run of the model for some specified number of periods is initiated by the command GO. Another command is available to change model parameters; this is the modify capability. The MODIFY command allows the manager to change all or some values of a vector or matrix by multiplication of a constant that is specified on-line. All changes need not be made at the beginning of a run. The model can be stopped after some number of periods and, after changes in the model parameters, the RESUME command continues the remainder of the run with the revised value. The strongest command capability is SEARCH. The search command allows the manager to specify a number of alternate levels of each variable to be examined and the size of the step between each of the values. After the computer reports the estimated search time, the manager may initiate the search and the program finds the best alternative by examining all combinations of the values the manager asked to be examined. The manager can examine the detailed results of this search by the use of the DISPLAY command and can then continue the search over alternate ranges and smaller increments.

The final commands of the program are INPUT and OUTPUT, which cause a copy of the stored values to be read in from a file or written out onto a file.

This type of conversational ability is satisfactory, but the state of the art is moving rapidly, and it soon will be feasible to use graphical devices to display and update matrices and vectors. Graphical presentation is more meaningful to most managers and will enhance their willingness to use this model and their understanding of the system.

### APPLICATION AND TESTING

THE MODEL-BASED information system proposed in this paper has been applied to the analysis of a new frequently purchased consumer product introduced by a medium-sized firm. The firm had test marketed the product in three cities and had collected all the information recommended for the data bank except the test-city consumer panel. They did, however, use very detailed monthly questionnaires, and it was possible to determine trial, repeat, and frequency rates from these questionnaires by examining on a disaggregate basis the changes in usage reported each period. This application will be described by reporting briefly (1) some examples of the insights gained from the test data by use of the model, (2) the testing of the model on the test-market periods, (3) the use of the model in making the go national decision, (4) the accuracy of the model in predicting national market shares, and (5) the adaptive use of the model in diagnosing the recommended solutions to national introduction problems.

The testing was carried out after the product had been introduced nationally for six months. So the testing was not 'live testing' until after that time. The test-market analysis, of course, used only test data.

#### *Interpreting Test-Market Data*

In deriving inputs for the model by applying the statistical procedures outlined in the statistical-bank section of this paper, several important behavioral insights were gained. First, the use of Datanal<sup>[23]</sup> to classify buyers by purchase history revealed that the trial rate for the brand was low (over-all 2 percent of the trial model population/month) and that the repeat rates were high (60 percent in the preference model, 70 percent in the loyalty I model and 80 percent in the loyalty II model). The repeat rate indicates high user satisfaction and a potentially strong brand if the trial rate can be established at a profitable level. In addition, it was found that the trial rate was higher in the first two months than in later months (3 percent in the first two months and dropping to 1.5 percent by the fifth month). This decreasing trial rate could be explained by the hypothesis that innovators are more trial prone, so, as the innovators move through

the trial model, the trial rate falls to levels of the majority of the consumers. The understanding of this aspect of the diffusion process is important, since it warns against over-optimism because of high initial sales.

To determine the in-store effects of price on trial [ $\overline{\text{RPDIFT}}$ , equation (9)], disaggregated store data in the three cities for the first three periods were used. Regressions of market share of the new product against the price difference between the new product and the standard price of the older competitive product in each store were carried out; they were significant at the 1 percent level, as were the  $t$  statistics for the coefficients. The single best expression for  $\overline{\text{RPDIFT}}$  obtained from the regressions and managerial judgment was

$$\overline{\text{RPDIFT}} = 1.3 - 1.5 [(PR - SPR)/SPR],$$

where

PR = price of product by our firm,

SPR = standard price of the old product.

This result implies that at higher price differentials fewer people exercise their intent. This is as economic theory would suggest, but there had been the belief in the company that consumers were judging the quality of the product by its price, and therefore a premium price had been established for the product. If this had been so, the higher prices would not have reduced the trial rate. The regression coefficient was confirmed by regressions in each individual city, store type, and period.

The effects of advertising were obtained from regressions of sales versus advertising levels between cities and over time. Six alternate multivariate lagged models were run and 1 to 5 percent significance was found for the advertising elasticities. The carryover effects were small and not significant, apparently because of the rapid forgetting rate of consumers for this type of advertising. A managerial review of the regression values indicated that the best estimate of the elasticity of advertising was +0.3.

These three examples of the specific input analysis supply the reader with a feeling for the general input-generation approach. The data were exhausted for information, and managerial judgment was used to interpret the results and obtain the best model inputs. This was a very time consuming process and required extremely close cooperation between a statistician, a market researcher, a brand manager, and a model builder. In addition to the best estimate, confidence intervals were prescribed, so the uncertainty about the sales forecast could be imputed to the risk associated with the product.

In this application it was found that the model fostered a systematic review of the test data and a more objective and analytical examination of

the diffusion process than had been undertaken under existing procedures. The new insights gained from the generation process were also found to be useful to the brand managers in sharpening their understanding of underlying market processes.

### ***Model Accuracy in Duplicating Test-Market Shares***

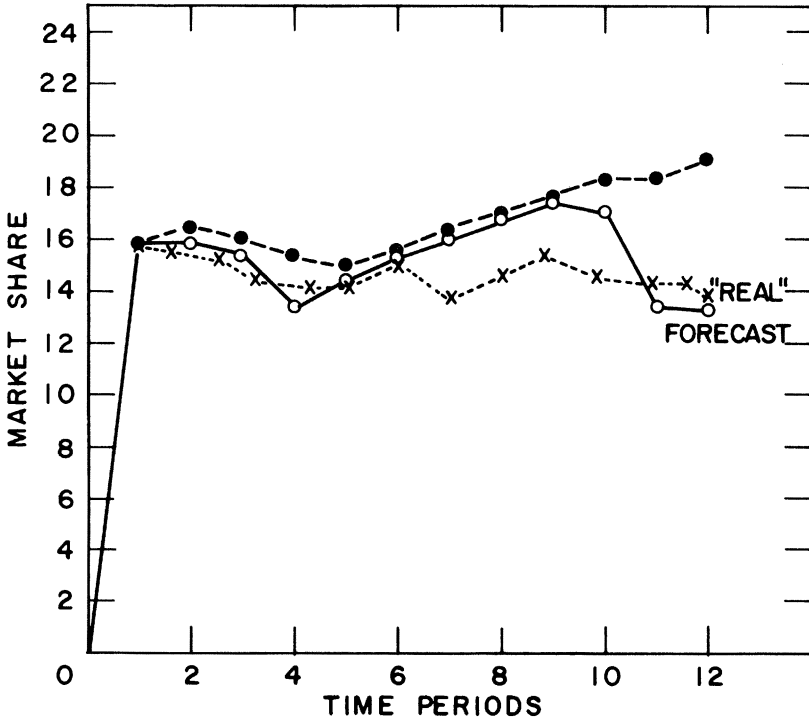
The normative model proposed in this paper should have descriptive adequacy if it is to be a useful guide to strategy determination and adaptive planning. One test of descriptive adequacy is to use the data collected in the test market to estimate the model's parameters and then compare the forecast results with actual results. This is a weak test, since it uses the same data base for estimation and testing, but it is a step in validating the prior hypothesis of the world as described by the model.

If the input has been accurately obtained and the model structure is valid, the model should be reasonably accurate in duplicating the market shares that are observed for the brand in the test market. The model generates the market share, given the behavioral-process input and the firm's and its competitor's controllable variables. In this test market, as often happens in product tests, the competitor attempted to confuse the test-market results by doubling his advertising and sampling 25 percent of the market with a regular-size container of his product. Figure 5 shows the test-market share predictions if the test had accurately depicted the planned national strategy. The share started high, but decreased as the innovators moved out of the trial model, then a steady growth was predicted due to the high repeat rate and stabilization of the trial rate. Figure 5 also shows the prediction when the competitor doubled his test-city advertising in periods 2, 3, and 4, and sampled heavily in period 2. The decrease in shares in periods 10, 11, and 12 was due to our phasing out of advertising and the completion of test marketing. The real market shares in Fig. 5 are based on the market shares in the samples of audited stores in the cities. The test forecast with competitive interference matches closely the real market shares, particularly in the first six months. In the later periods there is a spreading between the real and predicted shares; this is due to a failure of the model to predict the downturn in period 7. There is no explanation available for this downturn, but perhaps some competitive action had occurred that was not observed, or the nonrandom sample of audited stores was subject to a bias. It is encouraging, however, that the slopes of the real and predicted shares are similar after the dip in the real share. The match between the predicted and real shares was deemed reasonable by management, given the input accuracy and the accuracy of the methods for measuring 'real' market share. The test-market testing of the model indicated that the model, which was judged

by management to have face validity, also possessed descriptive adequacy in terms of the criteria set by management.

**The GO National Decision**

The decision to introduce the product should be made on the basis of the differential profit it will generate for the firm compared to its risk and



**Fig. 5.** Model testing: Test-market data.  
 ●-●-●=forecast with no competitive interference  
 ○-○-○=forecast with interference from competitor and phaseout  
 x--x--x=observed market share

investment in the product. This requires a forecast of national market share and sales. The behavioral-process model can generate this forecast on the basis of the test-market estimates of the model's parameters adjusted for any differences that may be expected between the test and national responses. Usually some adjustments are necessary, since the test cities are usually small or medium-sized cities like Syracuse or Peoria, which are not representative of the national response to the product. For example, distribution is almost always above the national level for each month after

introduction. In addition, the advertising response is usually overstated, since the usual translation of a national campaign overstates the relative competitive advertising pressure. Furthermore, people in smaller cities may not respond in the same way as big city residents who have developed more callousness to advertising. In this application, management made the following adjustments to reflect differences between test and national behavioral responses: (1) trial rates for each awareness class were reduced 10 percent, (2) the effectiveness of advertising in creating awareness was reduced 10 percent, (3) the proportion of people who convert intent into action was reduced 10 percent, (4) the initial levels of distribution were lowered to reflect expected national levels of availability at introduction, and (5) the starting point of the campaign was delayed because national plans called for a later time of introduction than in the test.

Under these conditions and the existing national plan, the forecast of national sales indicated a cash-flow contribution to the firm of \$1,130,000 in the first three years. Discounted at the firm's target rate of return of 40 percent per year, this cash flow yielded a present value of \$414,000. When this discounted differential profit was compared to the initial investment of \$300,000 and the uncertainties described by a subjective distribution of likely sales results, there was a 51 percent chance of achieving the target rate of return on investment in three years (*see* reference 38 for the details of this procedure). This result was not sufficient to justify a go decision. But these existing reference plans did not reflect the best strategy for the brand. Utilizing the SEARCH option of the program and examining over 100 strategies, we found that 15 percent lower prices increased the discounted profits to \$706,000. The advertising level specified in the reference plan was found to be at the best level when lower prices were utilized. The iterative search produced a strategy that represented a 70 percent increase in profits. The lower prices specified in the 'best' strategy reduced the number of people who would not exercise their intent to try [*see* equation (9)] and increased the in-store effectiveness as visualized by preference and loyalty buyers [*see* equations (17) and (18)]. Even at the higher profits, however, there was only a 54 percent chance of achieving a 40 percent rate of return on investment in three years.

The initial test of the new-product information system was carried out after the product had been in national marketing for six months. The go decision had been reached on the basis of subjective forecasts of a market-share growth rate that was considerably more optimistic than the model's prediction. The product was introduced at the planned premium prices, so the recommended strategy and profit increase have not been tested, and the profit increase must be termed a predicted increase. The model would *not* have recommended a go decision at the old planned levels, and even

with a better strategy would not have recommended introduction, since the probability of returning the target rate of return was below the firm's go criterion of 65 percent. A 65 percent probability of achieving the return-on-investment (ROI) objective could be achieved if a much better advertising appeal could be found. It would have to create 25 percent better awareness for the same dollar expenditures and a 25 percent higher intent-to-try rate for people with specific appeal recall. If a campaign of this quality could be devised, the appropriate advertising budget would be the same level as for the old campaign. The use of the search option indicated that decreasing the budget 10 percent would reduce profits 7 percent, that increasing the budget 10 percent would reduce the profits 1 percent, and that increasing the budget by 20 percent would reduce the profit 2.5 percent.

In summary, the model indicated that: (1) it would not be appropriate to introduce the product at the reference strategy, (2) 70 percent more discounted differential profit could be obtained from a better strategy, and (3) even at the better strategy the product should not be introduced. The model, using only test data, would have recommended that the marketing be improved before introduction and indicated that a better advertising appeal could generate the needed improvement.

### ***National Introduction Testing and Model Accuracy***

Since the product used for testing the model had already been introduced nationally, the forecasting of the model and its problem-finding capabilities could be tested, even though at the firm's strategy the model could not have recommended a go decision. The same data collected in the test market were collected during national introduction on a sampling basis. This enabled the behavioral-process parameters to be monitored during early introduction.

Within a few weeks of introduction, feedback from salesmen indicated the product was 'not moving.' The causes of this problem were found by examining the results of the national awareness and usage questionnaires carried out four weeks after introduction. These surveys showed that the awareness rates were down 20 percent from the predicted value and that the trial rates for those who were aware were 10 percent below expectation. The source of the reduction of the conditional trial rate was that the innovators nationally were not responding as rapidly as in the test cities. The 20 percent reduction in awareness in part was due to an error in translating the national advertising budget to the test-market cities. Too much advertising was inserted and the observed test levels were therefore artificially high. It is moot whether the use of the information system would have found this error before the go national decision was found; however, it is my opinion that in generating the input for the model, the examination

of the relative dollar expenditures would have resulted in a good chance (greater than 75 percent) of finding the translation error. The remaining reduction in awareness seems to have been due to a low national response to the advertising. The firm responded to this information by doubling advertising.

At the beginning of the third month of national introduction the major competitive firm unexpectedly introduced a brand to compete directly with our firm's new product. They backed this introduction with a 50 percent increase in their advertising level. This new-product advertising lowered our trial rates [see equation (6)] and reduced the proportion of people in the preference model who translated preference to intent to repurchase [see equations (15) and (16)]. These effects were monitored in the second national awareness survey. This survey was carried out ten weeks after introduction.

This three-city awareness survey also indicated some behavioral changes in addition to the effects of the competitor's new product. In particular, based on a comparison of the response levels in the cities, it was found that the awareness response function had shifted back to the level specified prior to introduction. The trial rates for the specific awareness classes also returned to their expected levels. This recovery was apparently due to the innovators being held out of the market by the initially low awareness levels and entering later than expected. The slow start of the product caused the innovators to spill over into the first five months rather than just the first three months, as had been observed in the test cities.

Six months after introduction, media audits showed the competitor had become very aggressive and had doubled his advertising relative to expectations. This new competitive rate was nearly equal to the total industry advertising in the previous year. The firm responded to this competitive activity with a continued high level of advertising in periods 5, 6, and 7, but had to reduce spending in periods 8, 9, and 10, since they had depleted the product's advertising budget. In periods 8, 9, and 10 the competitor also reduced his rates of advertising to his previous level.

The accuracy of the model in duplicating the actual national introduction market shares is shown in Fig. 6. The real market shares are based on Nielsen store audits and the model predictions are based on the prior test-market estimates updated for the changes in national environment described in the previous paragraphs. The model seems to be very accurate in its updated forecasts. These forecasts were made in the ninth month after introduction, but before the Nielsen market shares for months 8 and 9 were available. These forecasts do not reflect live forecasting tests for months 1 to 7, but month-8 and -9 tests are future forecasts based only on past data. The model predicted a downturn in the share for months 7, 8, and 9. Subsequently, the Nielsen market-share report showed this to be

accurate not only to the extent of predicting the turn, but also the amount of the drop. It should also be pointed out that the model was much better than management's existing procedures, which were in error by over 100 percent. Model testing also was carried out at the microlevel. For example, the growth of availability predicted by the model closely matched the Nielsen measurement of availability. The testing of the model on the national data indicated it to be valid in terms of management's standards of the accuracy required in a new-product decision model.

After testing on the basis of national data, the model served to analyze the decision to drop or to continue the brand. It showed that, if the price level were reduced as originally recommended, and if a new, 40 percent

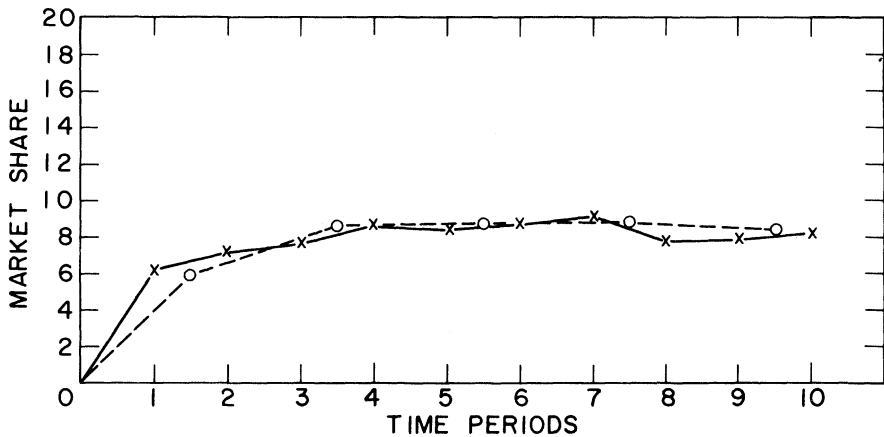


Fig. 6. Model testing: National introduction data.

x-x-x-x = model prediction

o-o-o-o = observed Nielsen market share

better, advertising campaign could be mounted, the brand would respond, achieve a 19 percent market share, and return \$2,000,000 in cash-flow profit in three years. These are essentially the same changes that the model would have originally required for a go decision, and it is reasonable to say that the model could have saved the firm a year of painful and highly unprofitable national experience.

### ***Adaptive Use of the Model during National Introduction***

During national introduction the model can serve as an adaptive mechanism. In this application, the data bank developed on the basis of national experience was used to diagnose basic problems, update the model's parameters, and search for a best response to the new information and the diagnosed problems.

The first new information was contained in the first month's national

awareness questionnaires, and it indicated that the advertising response function was lower than expected and that the trial rates were below expectation. The SEARCH capability of the model was utilized to examine alternate advertising levels assuming the best price (15 percent lower than reference) had been established for the product. It indicated that the best advertising strategy was to hold to the original plan. In contrast, the firm actually doubled advertising. The model indicated this would reduce profit by more than \$200,000.

The second set of new information was monitored in period 3. It indicated that the competitor had introduced a new brand and backed it by a 50 percent increase in advertising. At this same time, the second national awareness questionnaire indicated trial rates and the advertising response function had recovered to their expected levels. As mentioned previously, this was diagnosed as the late arrival of the innovators, and so the period 3, 4, 5, and 6 trial rates were raised 10 percent from their reference values to reflect the spill-over of innovators into later periods, a decision that was based on subjective managerial judgment. The search capability was again used, and an increase of 20 percent in advertising and a 10 percent reduction in price were found to be the best responses to the increased competitive activity and the basic behavioral response changes. The remainder of the adaptive testing was based on these changes having been implemented in period 4. The price change could have been implemented by a price-off deal.

In period 6 the national media audits indicated that the competitor had doubled his advertising expenditure. Since it was felt that this was a short-run strategy change, the model was updated by increasing the competitive expenditures only in periods 6, 7, and 8. The best response to this aggressive competitive action was to hold to the previously recommended level (20 percent more than reference.)

In period 8 the media audits reflected the competitor's return to the previous level (50 percent greater than reference) and the best response to this was to reduce our advertising 20 percent. This decrease was implemented in period 9.

The adaptive testing procedure for the first 10 periods and the projected results, based on the assumption that the period 9 strategy was used until period 36, generated a cash-flow profit of \$2,000,000. The company's actual strategy of higher prices and its nonoptimal adaptive strategy would have generated only \$500,000, so the combination of the better introductory plan and the national adaptive strategy determination generated an estimated additional \$1,500,000 of cash-flow profit. Since the go national lower price strategy was estimated to add \$600,000 of cash-flow profit, it appears that the use of the adaptive capabilities of the model is at least as

rewarding in terms of profit improvement as the GO national decision search capability.

### SUMMARY

THIS PAPER represents an attempt to integrate behavioral theory within a normative mathematical model for use in the analysis of frequently purchased consumer goods. The behavioral-process macromodel reflected the consumer decision process of starting at awareness, continuing to intent, search, choice, and ending in word-of-mouth generation and forgetting. This process was described in five purchase-history classes: trial, preference, loyalty I, nonloyal, and loyalty II. In each class the effects of the controllable parameters of the firm were emphasized so the model would have the power to recommend. Advertising creates a compatibility of the innovation to the buyer and an awareness of the felt needs it might fulfill. The distribution of samples is an attempt to show how the product fulfills needs and bestows benefits. Price is a factor in the relative advantage of the product, while sales effort affects the availability of the product to potential adopters. The formal mathematical statements of these phenomena represent a set of hypotheses of how the market operates. The use of the model over time with the suggested data base can help validate the market mechanism. This understanding and learning about the market and its acceptance mechanisms are the keys to successful new-product analysis.

The behavioral-process macromodel was positioned within an information system consisting of the model, a data bank, statistical bank, and input/output capability. The contents of the model's behavioral input requirements led to a specification of the data bank and statistical bank. This specification fosters an efficient use of data, because consideration of the disaggregated raw data is necessary in generating the response parameters. These statistical estimates, when combined with managerial judgment, represent the model's input. The model was placed in an on-line conversational program called SPRINTER Mod III, which allows a manager to DISPLAY, UPDATE, and MODIFY the data. He can also initiate a man-machine heuristic SEARCH for the best strategy alternatives and thereby utilize the normative power of the system.

The outputs of the model are: (1) behavioral insights into the test-market product environment, (2) a specification of the best strategy and its profit and risk implications, (3) a recommendation of GO, ON, or NO for the product, and (4) an adaptive capability to diagnose national introduction problems, generate updated forecasts, and recommend strategy responses to the national changes. Initial and limited testing of the model on one product indicates that it can accomplish these objectives and substantially

improve profits, and that it is reasonably accurate in forecasting market shares for a new frequently purchased consumer product.

After an initial model development and programming cost of \$200,000, the cost of applying this model on a continuing basis is estimated at \$25,000 per product in addition to the data-collection costs. The variable cost represents about 30-50 percent increase above the usual costs of test marketing, assuming the information required for the data bank is already being collected. In the author's opinion, this cost seems reasonable when compared to the potential to increase profits demonstrated in the test example (greater than 50 percent) and the possibility of preventing multi-million-dollar new-product mistakes. In order to provide an evolutionary approach to the system that aids in implementation and lowers the magnitude of resource commitment, two more elementary versions of the model exist. SPRINTER Mod I (see Urban<sup>[41]</sup>) is a very simple statement of the depth-of-class and behavioral-trial process. It has only thirteen inputs and requires only a small data base. SPRINTER Mod II is more elaborate and begins the evolution towards the complexity in Mod III. With the three models, users can select the best cost/benefit level of detail and data that best fit their budget and management.

## APPENDIX

### HYPOTHETICAL ON-LINE COMPUTER SESSION WITH SPRINTER: MOD III

The following code is used in the computer print-out and accompanying comments shown below:

✓ = data typed by manager; all other data is model output.

[ ] = comments about program to guide in interpretation.

```
RESUME SPRINTER

EXECUTION.
*
✓ INPUT...USE NATIONAL FORECAST DATA BANK      [Request to input test market data
GIVE INPUT TAPE NUMBER                          stored on file 66]
✓ 66

*
✓ GO...RUN 36 MONTHS                             [Forecast national environment on basis of test data]
TDDPRF = .523E 06, FSSP = 8, P(TGT-QBK) = .49844, P(PGT-RR) = .51032

[TDDPRF = total discounted differential profit
FSSP = first self sustaining period
P(TGT-QBK) = probability of achieving target payback
P(PGT-RR) = probability of achieving ROI objective]

*
✓ DISPLAY MARKET SHARE BY MONTH
✓ 273
MONTH
+
✓ 0

[273 is the code number for market
share, "0" indicates all periods]
```

MONTH						
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30	31	32	33	34	35
36						
.455E-01	.564E-01	.575E-01	.509E-01	.482E-01	.518E-01	.560E-01
.605E-01	.661E-01	.696E-01	.693E-01	.739E-01	.727E-01	.789E-01
.880E-01	.894E-01	.932E-01	.940E-01	.954E-01	.952E-01	.102E 00
.105E 00	.956E-01	.998E-01	.895E-01	.950E-01	.106E 00	.107E 00
.112E 00	.114E 00	.116E 00	.119E 00	.126E 00	.128E 00	.123E 00
.127E 00						

✓MODIFY -- REDUCE OUR SUGGESTED RETAIL PRICE BY 10%

✓140 COMPETITOR

+  
✓1  
=  
.90

Simulation of lower price -  
MODIFY command multiplies old  
value by specified constant  
(.90 in this case)

\*  
✓GO SIMULATE LOWER PRICES FOR 36 PERIODS  
IDDPRF= .750E 06,FSSP= 8,P(TGT-PBK)=.51985,P(PGT-RR)=.54927

✓UPDATE...ADD SAMPLING OF 750,000 IN EACH OF FIRST THREE MONTHS

132  
MONTH

Adding samples by updating sampling variable  
to desired level

+  
✓-1  
FIRST MONTH  
1  
LAST MONTH  
3  
COMPETITOR

-1 indicates a range of months is desired

+  
✓1  
=  
✓750000.

\*  
✓DISPLAY SAMPLING OF OUR FIRM

✓132  
MONTH

+  
✓-1  
FIRST MONTH  
✓1  
LAST MONTH

Display of samples to see update is as desired

✓5  
COMPETITOR  
+  
✓1

Competitor 1 is our firm

COMPETITOR	MONTH				
1	2	3	4	5	
1	.750E 06	.750E 06	.750E 06	.000E 00	.000E 00

\*  
 ✓GO...RUN 36 MONTHS  
 TDDPRF= .367E 06,FSSP= 8,P(TGT-PBK)=.487\*7,P(PGT-RR)=.50700

\*  
 DISPLAY SAMPLE USAGE RATE  
 23  
 MONTH  
 +  
 I

Preparation for sensitivity test of different usage rate and sample cost

SEGMENT                      MONTH  
 1                      .330E 00

\*  
 ✓DISPLAY SAMPLE UNIT COST  
 ✓112

1                      .250E 00

\*  
 ✓UPDATE...REDUCE SAMPLE UNIT COST TO 15 CENTS  
 ✓112  
 =  
 .15

\*  
 ✓GO...RUN 36 PERIODS  
 TDDPRF= .582E 06,FSSP= 8,P(TGT-PBK)=.49947,P(PGT-RR)=.52957

\*  
 ✓INPUT...RESTORE FORECASTED NATIONAL DATA BANK  
 GIVE INPUT TAPE NUMBER  
 ✓66

\*  
 ✓U SET TO RUN FOR ONLY 11 MONTHS  
 ✓4  
 =  
 ✓11

Update end period to 11; Note only first letter of work update is needed.

\*  
 U SET PRINT OPTION  
 63  
 1 TO 7  
 +  
 5  
 =  
 0  
 S= 71.00

Set print option 5 to print out model sales and populations of models by period.

\*  
 ✓GO...RUN FOR 11 MONTHS

MD	S	TIBUY	TPBUY	TLBUY	TGTGR	NTRIAL	NPREF	NLOYAL
1	1	.240E 06	.000E 00	.000E 00	.170E 08	.167E 08	.000E 00	.000E 00
2	1	.300E 06	.539E 04	.000E 00	.173E 08	.170E 08	.240E 06	.000E 00
3	1	.262E 06	.130E 05	.279E 03	.153E 08	.148E 08	.531E 06	.539E 04
4	1	.217E 06	.239E 05	.992E 03	.153E 08	.145E 08	.773E 06	.182E 05
5	1	.180E 06	.353E 05	.252E 04	.146E 08	.136E 08	.956E 06	.413E 05
6	1	.183E 06	.463E 05	.507E 04	.146E 08	.134E 08	.109E 07	.747E 05
7	1	.188E 06	.579E 05	.881E 04	.147E 08	.133E 08	.121E 07	.117E 06
8	1	.193E 06	.691E 05	.139E 05	.147E 08	.132E 08	.133E 07	.169E 06
9	1	.188E 06	.787E 05	.205E 05	.140E 08	.123E 08	.145E 07	.229E 06
10	1	.187E 06	.827E 05	.286E 05	.140E 08	.121E 08	.155E 07	.295E 06
11	1	.203E 06	.862E 05	.375E 05	.152E 08	.132E 08	.164E 07	.361E 06

```

*
TTBUY = no. of buyers      TGTGR = no. in target group
      in trial class       NTRIAL= no. in trial class
TPBUY = no. of buyers in  NPREF = no. in preference class
      preference class     NLOYAL= no. in loyal class
TLBUY = no. of buyers in
      local class
    
```

```

: U SET FOR SINGLE MONTH RUN
4
=
. 1
    
```

```

*
GO...RUN ONLY FIRST MONTH
MD S  TTBUY  TPBUY  TLBUY  TGTGR  NTRIAL  NPREF  NLOYAL
1 1  .240E 06  .000E 00  .000E 00  .170E 08  .167E 08  .000E 00  .000E 00
    
```

```

*
✓ DISPLAY # AD OR APPEAL A#ARE IN TRAIL MODEL AFIER ADV EXPOSURES
✓157
    
```

These displays show depth of detail in retrieving behavioral data.

SEGMENT

1 .403E 07

```

*
✓ DISPLAY # #ITH INTENT TO TRY OUR BRAND IN FIRST MONTH
✓159
    
```

SEGMENT

1 .873E 06

```

*
✓ DISPLAY # #ITH INTENT TO TRY OUR BRAND IN FIRST MONTH (BY AWARENESS CLS)
✓158
    
```

AWARENESS CL

SEGMENT	1	2	3	4	5	6	7
1	.000E 00 .000E 00	.220E 05	.297E 06	.424 06	.131E 06	.000E 00	.000E 00

```

✓ DISPLAY # WHO HAD INTENT TO TRY OUR BRAND AND WHO FOUND IT IN A STORE
✓162
    
```

STORE TYPE

1	2	3	
1	.283E 06	.657E 05	.668E 05

\*  
 ✓DISPLAY # WHO ACTUALLY BOUGHT OUR BRAND DURING FIRST MONTH BY STORE TYPE  
 ✓235

STORE TYPE

+  
 ✓0

SEGMENT	STORE TYPE		
	1	2	3
1	.163E 06	.379E 05	.386E 05

\*  
 ✓DISPLAY # IN AWARENESS CLASSES OF TRIAL MODEL AFTER FORGETTING  
 ✓267

AWARENESS CL

+  
 0

SEGMENT	AWARENESS CL						
	1	2	3	4	5	6	7
1	.151E 08 .000E 00	.942E 06	.227E 06	.249E 06	.216E 05	.136E 06	.464E 05

\*  
 \*  
 ✓SEARCH...TEST VARIOUS PRICE, ADVERTISING MIXES FOR MAX. PROFIT

VARIABLES ARE  
 (AD,PR,SM,CP,DL,SC)

Search all combinations of three levels of Price and three of Advertising and report best results

WSSS,DDD  
 ✓PR 3 .10                   THREE STEPS OF 10%  
 ✓AD 3 .20                   ADV ALSO THREE STEPS, BUT 20%

NR OF COMBS= 9  
 ESTIMATED EXECUTION TIME= 45.00 SECONDS

TYPE 'GO' TO COMMENCE SEARCH,ELSE PUSH RETURN

✓GO...COMMENCE SEARCH

ADV	PRICE	SAMPLES	COUPONS	DEAL	CALLS	IDD	PROFIT
.80000	.90000	1.00000	1.00000	1.00000	1.00000	1.00000	530601.38
.80000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	320349.71
.80000	1.10000	1.00000	1.00000	1.00000	1.00000	1.00000	-98837.94
1.00000	.90000	1.00000	1.00000	1.00000	1.00000	1.00000	757512.13
1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	506272.05
1.00000	1.10000	1.00000	1.00000	1.00000	1.00000	1.00000	-8219.40
1.20000	.90000	1.00000	1.00000	1.00000	1.00000	1.00000	558293.65
1.20000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	294876.81
1.20000	1.10000	1.00000	1.00000	1.00000	1.00000	1.00000	-260795.16

BEST RATIOS ARE  
 1.00000   .90000   1.00000   1.00000   1.00000   1.00000   757512.13

OUTPUT THIS SESSION FOR FUTURE USE  
 GIVE INPUT TAPE NUMBER FOR NEXT SESSION  
 67

\*  
 P QUIT,

## ACKNOWLEDGMENTS

RICHARD KARASH and JAY WURTS programmed the model for the computer; BILL JOHNSON, ARMANDO PENA, and RICHARD RAYSMAN provided data-analysis assistance; and computer resources were supplied by the MIT Computation Center. Finally, great thanks are due to the to-be-unnamed firm that funded the research and supplied the test case.

## REFERENCES

1. A. E. AMSTUTZ, *Computer Simulation of Competitive Market Response*, The MIT Press, Cambridge, Mass. 1967.
2. S. BANKS, *Experimentation in Marketing*, McGraw-Hill, New York, 1964.
3. C. P. BONINI, *Simulation of Information and Decision Systems in the Firm*, Prentice-Hall, Englewood Cliffs, N. J., 1963.
4. R. A. BOWER, "Consumer Behavior as Risk Taking," pp. 389-398 in *Proceedings of the National Conference of the American Marketing Association*, American Marketing Association, 1960.
5. J. W. BREHM AND A. R. COHEN, *Explorations in Cognitive Dissonance*, Wiley, New York, 1962.
6. P. C. BURGER, "Developing Forecasting Models for New Product Introductions," pp. 112-118 in R. L. KING (ed.), *Proceedings of the National Conference of the American Marketing Association*, American Marketing Association, Denver, 1968.
7. N. P. CHAPANIS AND A. CHAPANIS, "Cognitive Dissonance: Five Years Later," *Psychological Bull.* **16**, 1-22 (1964).
8. A. CHARNES, W. W. COOPER, J. K. DEVOE, AND D. B. LEARNER, "DEMON: Decision Mapping Via Optimum GO-ON Networks—A Model for Marketing New Products," *Management Sci.* **12**, 865-887 (1966).
9. ———, "DEMON: Mark II External Equations Approach to New Product Marketing," *Management Sci.* **14**, 513-524 (May 1968).
10. ———, "DEMON: Mark II External Solutions and Approximations," *Management Sci.* **14**, 682-691 (July 1968).
11. A. CHARNES, L. LIGHT, L. PRINGLE, AND E. F. SNOW, "News Report," Carnegie-Mellon University Working Paper, Pittsburgh, Pennsylvania, May 1968.
12. D. F. COX AND S. RICH, "Perceived Risk and Consumer Decision Making," *J. Marketing Research* **1**, 32-39 (1965).
13. S. M. CUNNINGHAM, "Perceived Risk as a Factor in the Diffusion of New Product Information," pp. 698-722 in R. HAAS (ed.), *Proceedings of the National Conference of the American Marketing Association*, American Marketing Association, Indiana University, Fall 1966.
14. L. FESTINGER, *A Theory of Cognitive Dissonance*, Stanford University Press, Stanford, Calif., 1967.
15. ———, *Conflict, Decision, and Dissonance*, Stanford University Press, Stanford, Calif., 1964.
16. J. HERNITER AND V. J. COOK, "Microsimulation Evaluation of Advertising

- Budget Strategies," Paper presented at the International TIMS meeting March 27, 1969.
17. H. E. KRUGMAN, "The Impact of Television Advertising: Learning Without Involvement," *Public Opinion Quart.* **29**, 349-356 (1965).
  18. ———, "The Measurement of Advertising Involvement," *Public Opinion Quart.* **30**, 583-596 (1966-67).
  19. D. B. LEARNER, "Profit Maximization Through New Product Marketing Planning and Control," pp. 151-168 in F. M. BASS, C. W. KING, AND E. A. PESSEMIER (eds.), *Applications of the Sciences in Marketing Management*, Wiley, New York, 1968.
  20. J. D. C. LITTLE, "A Model of Adaptive Control of Promotional Spending," *Opns. Res.* **14**, 175-197 (1966), and "A Multivariate Adaptive Control Model," Sloan School of Management Working Paper 211-66, M.I.T., Cambridge, 1966.
  21. W. F. MASSY, "Stochastic Models for Monitoring New Product Introduction," pp. 85-112, in F. M. BASS, C. W. KING, AND E. A. PESSEMIER (eds.), *Applications of the Sciences in Marketing Management*, Wiley, New York, 1968.
  22. F. M. NICOSIA, *Consumer Decision Processes*, Prentice-Hall, Englewood Cliffs, N. J., 1966.
  23. J. R. MILLER, "DATANAL: An Interpretive Language for On-Line Analysis of Empirical Data," Sloan School of Management Working Paper 275-67, MIT., Cambridge, 1967.
  24. W. T. MORRIS, *Management Science: A Bayesian Introduction*, pp. 134-136, Prentice-Hall, Englewood Cliffs, N. J., 1968.
  25. M. Nakanishi, "A Model of Reactions to New Products," Ph.D. dissertation, University of California, Los Angeles, 1968.
  26. K. S. PALDA, *The Measurement of Cumulative Advertising Effects*, Prentice-Hall, Englewood Cliffs, N. J., 1964.
  27. ———, "The Hypothesis of a Hierarchy of Effects: A Partial Evaluation," *J. Marketing Research*, 13-25 (February 1966).
  28. E. A. PESSEMIER, *New Product Decisions: An Analytical Approach*, McGraw-Hill, New York, 1966.
  29. ———, P. C. BURGER, AND D. J. TIGERT, "Can New Product Buyers Be Identified?" *J. Marketing Research*, 349-355 (November 1967).
  30. D. T. POPIELARZ, "An Exploration of Perceived Risk and Willingness to Try New Products," *J. Marketing Research*, 368-373 (November 1967).
  31. W. F. POUNDS, "The Process of Problem Finding," *Industrial Management Rev.*, 1-19 (Fall 1969).
  32. R. E. QUANT, "Estimating Advertising Effectiveness: Some Pitfalls in Econometric Analysis," *J. Marketing Research*, 51-60 (May 1964).
  33. E. M. ROGERS, *Diffusion of Innovations*, The Free Press of Glencoe, New York, 1962.
  34. E. M. ROGERS AND J. D. STANFIELD, "Adoption and Diffusion of New Products: Emerging Generalizations and Hypotheses," pp. 227-250 in F. M. BASS,

- C. W. KING, AND E. A. PESSEMIER (eds.), *Applications of the Sciences in Marketing Management*, Wiley, New York, 1968.
35. D. C. SEARS AND J. L. FREEDMAN, "Selective Exposure to Information: A Critical Review," *Public Opinion Quart.* **31**, 194-213 (1967).
  36. J. N. SETH AND M. VENKATESAN, "Risk Reduction Processes in Repetitive Consumer Behavior," *J. Marketing Research*, 307-311 (August 1968).
  37. V. STEFFLRE, "Market Structure Studies: New Products for Old Markets and New Markets (Foreign) for Old Products," pp. 251-268 in F. M. BASS, C. W. KING, AND E. A. PESSEMIER, *Applications of the Sciences in Marketing Management*, Wiley, New York, 1968.
  38. G. L. URBAN, "A New Product Analysis and Decision Model," *Management Sci.* **14**, 495-517 (1968).
  39. ———, "An On-Line Technique for Estimating and Analyzing Complex Models," pp. 322-327 in R. MOYER (ed.), *Changing Marketing Systems*, American Marketing Association, 1968.
  40. ———, "New Product Decisions: Information Discounting and New Product Selection," Sloan School of Management Working Paper 292-67, MIT., Cambridge, 1967.
  41. ———, "SPRINTER mod I: A Basic New Product Analysis Model," pp. 139-150 in B. A. MORIN (ed.), *Proceedings of the National Conference of the American Marketing Association*, American Marketing Association, Atlanta, June 1969.
  42. D. J. WILDE AND C. S. BEIGHTER, *Foundation of Optimization*, Prentice-Hall, Englewood Cliffs, N.J., 1967.