Formal Models of Consumer Behavior: A Conceptual Overview
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INTRODUCTION

In the last ten years, there has been a great increase in building formal models of consumer behavior. By formal models we mean those models with an explicit structure, normally either mathematical or computer, as opposed to verbal models. These models have proliferated very rapidly and exist in a bewildering array of forms. The purpose of this paper is to give an overview of the field of formal consumer models and provide a framework for understanding the field and placing the many model types in perspective. Accordingly, the paper is much more conceptual than technical in nature.

We start by outlining a rough classification of model types, and describing these types. Next, the conceptual bases of the various model types are discussed and compared. This discussion considers such topics as the general world view of the modelers, necessary data properties, individual differences and aggregation, and model uses. Potentially useful interactions between model types are then discussed. Finally, prospects and problems for each model type are considered, and overall conclusions are drawn.

CLASSES OF FORMAL MODELS OF CONSUMER CHOICE

Formal models of consumer behavior may be roughly classified into four broad types: information-processing models, stochastic models, experimental and other linear models, and large-system models. The characteristics of models in each of these classes will be discussed in this section.

The discussion in this section is *not* intended as a literature review. Several good reviews already exist. The object of this section is to discuss the essential features of models in the various classes, in order to set the stage for the comparative discussions which follow.

STOCHASTIC MODELS[1]

A stochastic model generally consists of two important components—a model of individual behavior and a "rule" for aggregating these individual models. The individual model describes some aspect (e.g., brand choice, interpurchase time) of an individual consumer's purchase be-

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1. For a good review of particular stochastic models, see William F. Massy, David B. Montgomery, and Donald G. Morrison, *Stochastic Models of Buying Behavior* (Cambridge, Mass.: M.I.T. Press, 1970).

havior. This behavior is made an explicit function of a few (zero to two) of the *major* determinants of this aspect of behavior. All other determinants are accounted for by making the model stochastic. For example, in models of brand-choice behavior, the *probability* of purchasing brand *A* is modeled as a function of such determinants as the brand purchased last time, external time effects, the past history of purchases, or some combination of effects.[2] Other factors—for example, price—are not usually explicitly considered by the model.[3] However, since what is modeled is the *probability* of purchase, rather than the purchase outcome itself, such factors are implicitly considered because the model is stochastic.

The aggregation rule for these models usually takes one of two forms. The most straightforward approach is to assume that every individual is the same in all aspects of behavior. However, following some pioneering work by Morrison,[4] many of the current models assume that individuals are different with respect to some aspect of their behavior. That is, different individuals will react somewhat differently when subject to the same set of stimuli. The aggregation problem becomes more difficult in this case, and it is usually this difficulty which restricts the number and complexity of allowable individual differences. (This problem will be discussed further in the section on aggregation.)

Hence, stochastic models are characterized by (1) a willingness to use stochastic elements to handle behavioral complexity; (2) a concentration on broad, general determinants of behavior; and (3) a concern for aggregation to populations.

INFORMATION-PROCESSING MODELS OF CONSUMER CHOICE

One recent trend in formal models of consumer decisions has been the emergence of information-processing models. These models make the basic assumption that man receives continual information input from his environment and processes this information as an integral part of making choices. In particular, an individual has certain rules by which he processes and manipulates information, and these rules specify his decision

2. Examples of these model types are Frank Harary and Benjamin Lipstein, "The Dynamics of Brand Loyalty: A Markov Approach," *Operations Research* (January–February 1962), pp. 19–40, and Donald G. Morrison, "Testing Brand Switching Models," *Journal of Marketing Research* (November 1966), pp. 401–9 (brand purchased last time); David B. Montgomery, "A Stochastic Response Model with Application to Brand Choice," *Management Science* (March 1969), pp. 323–37 (external time effects); James Carman, "Brand Switching and Linear Learning Models," *Journal of Advertising Research* (June 1966), pp. 23–31, and Alfred A. Kuehn, "Consumer Brand Choice—a Learning Process?" *Journal of Advertising Research* (December 1962), pp. 10–17 (past history of purchases); and, finally, J. Morgan Jones, "A Dual-Effects Model of Brand Choice," *Journal of Marketing Research* (November 1970), pp. 458–64 (combination of effects).

3. For an exception, see L. G. Telser, "The Demand for Branded Goods as Estimated from Consumer Panel Data," *Review of Economics and Statistics* (August 1962), pp. 300–324.

4. Morrison.

processes. It is deemed essential by the theory to actually model all of the detailed rules used.

Much of the early work in this field was done in psychology and computer science. Newell, Shaw, and Simon[5] assert that the basic components of information-processing models are (1) a number of memories containing symbolic information; (2) a number of simple primitive information processes, which are building blocks for more complicated processes; and (3) definite rules for combining simple processes to yield whole programs, or coherent wholes, of processing. This program then generates observable behavior.

In contrast with the stochastic consumer models, information-processing models assume that the rules they contain can be formulated deterministically, without probabilistic notions. Also, information-processing models take as their province the particular individual. Each subject requires a possibly different model. These models are obtained by having each subject think out loud while he is performing the behavior being modeled. Such a record is termed a protocol. Thus, Bettman had his subjects think out loud as they were in the actual process of shopping in order to collect his data.[6] Given these data, a model of how the subject processes the data from the environment to make a choice is constructed. All of the detailed processes that can be inferred are modeled, if possible. This inference process from the protocol is a difficult task, and only recently have structured and formal methods been proposed.[7]

Particular information-processing models of consumer choice are few. Bettman modeled two consumers' choices for grocery products.[8] Alexis, Haines, and Simon modeled women's clothing decisions,[9] and Haines also modeled raincoat choices.[10] King developed an information-processing framework for consumer choice.[11] Recently, Russ has developed models of choices of several subjects for small durable goods in a laboratory setting.[12] Finally, Clarkson modeled a trust investment officer's stock purchases.[13]

5. Alan Newell, J. C. Shaw, and Herbert A. Simon, "Elements of a Theory of Human Problem Solving," *Psychological Review* (May 1958), pp. 151–66.

6. James R. Bettman, "Information Processing Models of Consumer Behavior," *Journal of Marketing Research* (August 1970), pp. 370–76.

7. Alan Newell, "On the Analysis of Human Problem Solving Protocols" (working paper, Carnegie-Mellon University, 1966).

8. Bettman, "Information Processing Models."

9. Marcus Alexis, George Haines, and Leonard Simon, "Consumer Information Processing: The Case of Women's Clothing," *Proceedings of the American Marketing Association*, ser. 28 (1968), pp. 197–205.

10. George Haines, "Information and Consumer Behavior" (working paper, University of Rochester, July 1969).

11. Robert H. King, "A Study of the Problem of Building a Model to Simulate the Cognitive Processes of a Shopper in a Supermarket," in *Consumer Behavior: Learning Models of Purchasing*, by George Haines (New York: Free Press, 1969), pp. 22–67.

12. Frederick A. Russ, "Consumer Evaluation of Alternative Product Models" (Ph.D. diss., Carnegie-Mellon University, 1971).

13. Geoffrey Clarkson, *Portfolio Selection: A Simulation of Trust Investment* (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1962).

In summary, the major facets of information-processing models are (1) an assertion that individuals actively process information when making choices and that the processing rules used are to be modeled in as much detail as possible; (2) the belief that deterministic models are appropriate models of choice processes (rather than having probabilistic phenomena subsume detail, the detail itself is modeled); and (3) a concentration on models of particular individuals by using protocol data. Thus studies in this area use very small numbers of subjects (one or two, usually), and the models developed are highly idiosyncratic.

EXPERIMENTAL AND OTHER LINEAR MODELS

The models which we include in this classification are dissimilar with regard to content but have a common formal mathematical structure. Many experimental studies have been conducted on various aspects of consumer behavior. Because of a strong tradition of linear relationships imbedded in the statistical theories of multivariate analysis, several of these studies implicitly contain a linear model of behavior. In addition, other studies have explicitly stated a linear model.

We shall use a broad definition of linear relationships in this paper, such as $\log x + e^y$. Strictly speaking, these are additive separable relationships. We include these because the data are often transformed to obtain the best-fitting model. Mathematically, the model might be described as

$$f(y) = \sum_i g_i(x_i) + \epsilon,$$

where y is the dependent variable (aspect being modeled), the x_i are the independent variables (one or more other factors), and ϵ is a random element. This ϵ is included to account for the other factors which affect y but are not explicitly considered in the formulation. Most of these models are designed to represent the *market,* rather than the individual consumer.

Without close inspection, it is difficult to separate the studies containing implicit models from the set of all experimental models. Generally, these models describe one aspect of consumer behavior (e.g., market share of the brand) as a linear function of one or more other factors. One set of explicit linear models is the Fishbein-Dulany approach to predicting behavior and attitudes.[14] These models incorporate some data on individuals' inner states to predict behavior. This approach has been recently applied to marketing problems.[15] Day presents other linear attitude

14. Martin Fishbein, "Attitude and the Prediction of Behavior," in *Readings in Attitude Theory and Measurement*, ed. M. Fishbein (New York: John Wiley & Sons, 1967), pp. 477–92.

15. For examples, see Flemming Hansen, "Consumer Choice Behavior: An Experimental Approach," *Journal of Marketing Research* (November 1969), pp. 436–43; and Peter Sampson and Paul Harris, "A User's Guide to Fishbein," *Journal of the Market Research Society* 12, no. 3 (July 1970): 145–64.

models.[16] A second major set of explicit linear models consists of models of purchasing behavior using demographic and personality test scores as independent variables.[17] Finally, a third type of linear model is one in which independent variables are marketing variables, and sales or purchases are the dependent variable.[18] This brief characterization of linear models certainly does not exhaust the field, but it gives an idea of the range of models which have been developed. Note that these linear models are basically descriptive and are designed to represent the *market* or *population*, not the individual.

The main characteristics of these linear models are then (1) linear model structure, (2) inclusion of a stochastic error factor, and (3) subsuming of individual differences in a population or market orientation.

LARGE-SYSTEM MODELS OF CONSUMER CHOICE

The class of large-system models contains those models of consumer choice characterized by a broad general structure of postulated interrelationships, usually verbal, with a somewhat simplified formal model fit within this framework. Three main models of this type are considered in this paper: Amstutz; Farley and Ring's linear realization of the Howard-Sheth model; and Nicosia.[19] There is more formal mathematical diversity within this class of models than within the other model types. The modeling techniques themselves differ among all three models—they are, respectively, simulation, simultaneous linear regression equations, and a system of differential equations. The major coherence for this class is in the comprehensiveness of the underlying conceptual system, to which the model is a first approximation. These conceptual systems are all heavily based on the results of linear experimental models, used as data points for induction. Because the models differ, we will give a brief overview of each.

Amstutz's consumer-behavior model is a microanalytic simulation. By this is meant that there is a detailed specification of individual decision processes, which are aggregated. His consumer-choice model is rather involved, including marketing factors, attitudes, media communi-

16. George S. Day, *Buyer Attitudes and Brand Choice Behavior* (New York: Free Press, 1970).

17. Work in this area is well represented by William F. Massy, Ronald E. Frank, and Thomas Lodahl, *Purchasing Behavior and Personal Attributes* (Philadelphia: University of Pennsylvania Press, 1968).

18. For an example of this type of model, see Ronald E. Frank and William F. Massy, "Shelf Position and Space Effects on Sales," *Journal of Marketing Research* (February 1970), pp. 59–66.

19. Arnold E. Amstutz, *Computer Simulation of Competitive Market Response* (Cambridge, Mass.: M.I.T. Press, 1967); John U. Farley and L. Winston Ring, "An Empirical Test of the Howard-Sheth Model of Buyer Behavior," *Journal of Marketing Research* (November 1970), pp. 427–38; and Francesco Nicosia, *Consumer Decision Processes: Marketing and Advertising Implications* (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1966).

cations and word of mouth, and several other components. The model is probabilistic, with the response-probability generation functions being simple linear or exponential forms, for the most part. Amstutz also does not attempt to fit his individual models to specific consumers, but uses his population of individual models to attempt to fit aggregate data. Thus, like information-processing models, detailed models of the individual are developed. However, Amstutz's model differs sharply from information-processing models in the use of probability mechanisms and in developing generalized models of an individual rather than specific models for given individuals.

The Howard-Sheth verbal theory of buyer behavior[20] represents an extremely complicated theoretical system. Farley and Ring have developed a system of eleven simultaneous regression equations as a first empirical test of the theory. Thus they have built a simple formal model within the Howard-Sheth framework. Particular attention was paid to modeling the endogenous variables from the theory (e.g., attention, stimulus ambiguity, brand comprehension), although exogenous marketing and demographic variables were also included. Their linear model is probabilistic in the sense of including probabilistic error terms, and is a model for populations rather than for individuals. In the empirical test carried out, the findings for the endogenous variables were satisfactory, but the exogenous variable relationships and the overall goodness of fit were not. Much of the difficulty is attributed to problems of precise specification of complex variables and problems in measurement.[21]

Nicosia first develops a verbal and flow-chart model based on four fields, or building blocks.[22] Then he develops a system of differential equations whose variables represent the inputs and outputs of his four fields; thus the equations comprise a reduced formal model of his comprehensive scheme. Nicosia analyzes a system of four linear differential equations in some detail.[23] The variables involved are buying behavior, motivation, attitude, and advertising. Nicosia analyzes properties of the solutions of the system, both in equilibrium and over time. The model is deterministic rather than probabilistic. It is unclear what the model is intended to depict. It appears to model an average or generalized consumer. Nicosia has not attempted to apply the model to actual data. Measurement problems would seem to be severe in trying to apply the model.

In summary, the large-system models are characterized as formal models (1) corresponding to reductions of large and comprehensive verbal schemes of consumer choice processes, (2) having substantial measurement and estimation problems due to the abstraction and gen-

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

21. Farley and Ring, pp. 434–36.

22. Nicosia, pp. 155–57.

23. Nicosia, pp. 208–37.

erality in their variables, and (3) being more heterogeneous than the other model types.

Given this overview of classes of formal consumer models, we now turn to an examination of their underlying properties and concepts.

UNDERLYING CONCEPTS OF THE FORMAL MODELS

An attempt will now be made to outline some of the conceptual framework underlying the building of formal models, and to compare the model types outlined above according to this framework. Four basic areas are considered: (1) the general "world view" espoused by the model builders, (2) the type of data used and the method of collection, (3) how the problems of heterogeneity (individual differences) and aggregation of individuals are handled, and (4) how the models are intended to be used.

GENERAL WORLD VIEW

In this section many contrasts could be made. Only a limited subset will be examined here. All of these contrasts are interrelated, but we discuss them separately for the sake of convenience.

A somewhat subtle comparison can be made regarding the basic approach to model building espoused by the various formal consumer modelers. It is similar to the inductive versus deductive classification, but not the same. Information-processing modelers and large-system modelers take as given more a philosophy of model building than any particular model structure. Information-processing modelers consider the basic ideas of man as an information processor, and large-system modelers hold the concepts of system components and interrelations as their basic tenets. These philosophies then guide examination of data, and a particular model structure emerges. Many stochastic modelers, on the other hand, see modeling from a more formal structural point of view. A set of formal mathematical structures exists, and modeling problems become structural concerns such as parameter estimation and goodness of fit.[24] Some stochastic modelers, particularly Ehrenberg, object to this view and tend to let structure emerge from the data.[25] This difference, of course, is probably to some extent confounded with stage of development and model complexity. Information processing and large-system models are much more recent and complex, and hence a foundation of particular formal structures has not been developed.

A second major consideration is whether the modeler, for the pur-

24. The comparison made here is somewhat similar to the distinction in operations research between dynamic programming as a modeling philosophy and linear programming as a class of structurally well-defined models.

25. M. Bird, C. Channon, and A. S. C. Ehrenberg, "Brand Image and Brand Usage," *Journal of Marketing Research* (August 1970), pp. 307–14; and A. S. C. Ehrenberg, "Models of Fact: Examples from Marketing," *Management Science* (March 1970), pp. 435–45.

pose of his models, sees behavior as being probabilistic or deterministic. As mentioned briefly above, information-processing models assume that decision rules can be expressed by deterministic models. Nicosia also assumes no probability element in his differential-equation model. Stochastic models, of course, assume a basic probabilistic nature. The probabilistic element enters because not all factors are intended to be included by the modeler, particularly situational factors. Also, to some extent, it subsumes differences between individuals. Linear models, including the formal Farley and Ring realization of the Howard-Sheth model, also have a probabilistic element in that error terms are included to handle factors not accounted for by the model. Finally, Amstutz's models are in essence probabilistic, using simple stochastic response functions and a Monte Carlo procedure.

Another consideration is whether the individual or some population is the unit of analysis for any particular model. Here we have a clear split, as information-processing models consider the individual, whereas the other model types all consider populations. Amstutz considers generalized individuals, but his main interest is to fit aggregate population data. Related to this is the question of what processes are considered for inclusion in a model. In general, because of the interest in the individual, information-processing models are concerned with any decision rule that can be characterized, no matter how idiosyncratic. On the other hand, the other model types limit themselves to a selection of one or a few (most stochastic models) or several (large-system and linear models) rather general processes assumed to be universally present. Note that this contrast is rather deeply interconnected with general philosophies of model analysis—to use well-defined tools of analysis such as the stochastic and linear models employ, the models must be kept reasonably simple.

The time frame of reference varies for the model types. Most stochastic models and the Amstutz and Nicosia models are connected with behavior that occurs over time. They are in essence dynamic models. On the other hand, most linear models deal with a single experiment or at most a one-time change. Information-processing models also deal with the structure of decision rules at a given point in time. Although decision rules change, no attempt has been made to model change over time for consumer-decision-process models, although dynamic information-processing models have been developed in other domains.[26]

One final contrast may be briefly drawn. Information-processing, stochastic, the Nicosia, and the Amstutz models share a concern with the form of choice processes. For example, stochastic model builders concern

26. Goeffrey Clarkson, "Decision Making in Small Groups—a Simulation Study," *Behavioral Science* (July 1968), pp. 288–305; and Edward A. Feigenbaum, "The Simulation of Verbal Learning Behavior," in *Computers and Thought*, ed. E. A. Feigenbaum and J. Feldman (New York: McGraw-Hill Book Co., 1963).

themselves with the existence of purchase-event feedback and with the time span of memory (e.g., what past purchases affect the current purchase). Amstutz considers the form of his response functions.[27] Nicosia is concerned with the structure of feedback involving motivation, attitude, and behavior.[28] On the other hand, linear model builders do not envision consumers calculating linear model coefficients in their heads. Linear models are simply useful for predicting outcomes or for performing hypothesis tests. Matching actual choice processes is to some extent irrelevant.

DATA CONSIDERATIONS

Data collection is deeply entwined with the "world view" held, so the present discussion will amplify that of the last section to some extent.

Depending upon the model type, the level of detailed data required varies. Most stochastic models require only data on overt purchase responses. Some linear models also require only reasonably objective data.[29] However, some attitude models—particularly the Fishbein-Dulany models, the Farley and Ring linear realization of the Howard-Sheth model, Nicosia's model, and Amstutz's—require more subjective data on inner feelings and states. Finally, information-processing models require the most detailed data base. Not only are data on inner states required, but the sequential aspects of data are very important for inferring decision rules. Thus protocol data are very fine grained compared with data for other model types.

Another consideration as to type of data gathered concerns the content of the data. Most stochastic models do not include the effects of marketing variables, although there are exceptions.[30] On the other hand, some linear models,[31] information-processing models, and large-system models in general try to determine how marketing variables affect decisions. Hence, this type of data on marketing variables is required.

Time considerations are also important in data collection. Data can be taken on a one-time basis or over time. This is obviously closely related to the static or dynamic character of the models discussed in the last section. Stochastic models require data collected over time for the same individual, as found on panel data. The Amstutz model and the linear realization of the Howard-Sheth model also use over-time panel data.[32] Finally, although it has not been fit to actual data, the Nicosia model would certainly need data collected over time to fit its differential

27. Amstutz, pp. 386–91.
28. Nicosia, p. 197.
29. For example, Frank and Massy (n. 18 above).
30. See Massy, Montgomery, and Morrison (n. 1 above), pp. 428–40; and Telser (n. 3 above).
31. For example, Frank and Massy; or P. McClure and E. West, "Sales Effects of a New Counter Display," *Journal of Advertising Research* (March 1969), pp. 29–34.
32. Amstutz, pp. 383–85; Farley and Ring, pp. 437–38.

equations. Most linear models use only one-time measurements, as do most information-processing models.[33]

The structure inherent in the collection procedure offers a clear contrast. Information-processing models use protocol data, collected in a very unstructured manner (the subject is merely instructed to "think out loud" while making choices). Data for the other models are obtained from structured questionnaires or panel diaries. There has been some controversy in the psychological literature as to whether protocols represent behavior. Information-processing theorists have strenuously defended the process: "But if we had not recorded the things the subject said he was considering along with the things he actually did, the task would be hopeless. It is actually easier to simulate the person's spoken thoughts than to simulate only the decisions that appear in his behavior. Since thinking aloud permits more of the person's thought processes to project through the plane of perception, it helps to limit the variety of conceivable descriptions to a handful that are reasonably accurate."[34]

INDIVIDUAL DIFFERENCES AND AGGREGATION

As mentioned above, the model classes are differentiated by their assumptions about the individual. Information-processing models are designed to represent, in great detail, the decision processes of a single individual. On the other hand, most experimental and linear models never consider an individual per se, but only the collective behavior of all individuals in the market. Somewhere between these two extremes are stochastic models and large-system models. This section is devoted to a further discussion of these aspects for each group of models, and to some of the philosophical and practical questions which are raised by these differences.

Some model types may not be intended to model market behavior. However, if models which describe individual behavior *are* to be used for modeling market behavior, they must be aggregated in some way. Hence, let us now discuss the three major types of aggregation, since the type of aggregation used has strong implications for the way the modeler views individuals.

The most widespread aggregation technique is to assume that all individuals are homogeneous in their behavior. That is, the model which represents the behavior of consumer *A* can represent the behavior of consumer *B* equally well. Under this assumption the model of the population is essentially the same as the model of the individual.

The second technique for aggregation is that of microaddition. In this technique a (supposedly heterogeneous) population is divided into

33. However, Bettman uses measurement over time for his information-processing models.

34. George Miller, Eugene Galanter, and Karl Pribram, *Plans and the Structure of Behavior* (New York: Holt, Rinehart & Winston, 1960).

relatively homogeneous subgroups. Then representative individual models are developed for each subgroup. Presumably these representative models differ across subgroups. Aggregation then consists of combining the representative models, taking into account the relative sizes of the subgroups.

The third technique we shall call probabilistic aggregation. It assumes that individual models are heterogeneous in some aspect and that this heterogeneity is distributed over the population according to some probability distribution. For example, some parameter in the model may be assumed to have a beta distribution across individuals in the population.[35] This is, in a very real sense, a generalization of the microaddition technique, since it assumes that there will be a number of individuals with essentially the same model of behavior. *However,* unlike the microaddition technique, probabilistic aggregation can be applied to any given population. Microaddition, on the other hand, requires defining the subgroups which are to have representative models.

Having outlined the types of aggregation possible, let us now consider how the various model types aggregate consumers. To date, information-processing models have only been applied to individuals. No effort has been made to aggregate across individuals. One can wonder, of course, whether such aggregation would ever be possible, if every individual is truly different from every other individual. Some work has been done on measuring the similarity of decision nets.[36] This technique could be applied to a large-scale study of individuals, in an effort to develop relatively homogeneous subgroups to use with microaddition techniques. Perhaps some of the heterogeneity techniques would also be applicable here, although the technical problems of application seem very difficult.

At the other end of the spectrum are the experimental and linear models. Most of these ignore any consideration of individuals, and the few that consider a model of individual behavior also make the homogeneity assumption, so that there is basically no distinction between the market model and the individual model. Thus, these models are truly *market* models, with essentially no consideration of individuals.

The stochastic models represent a strange anomaly. Although they are treated as models of individual behavior which are aggregated over the population, few studies[37] make any attempt to verify the model of the individual. All others test only the model of the market obtained through the aggregation process. A serious question is thus raised as to whether these models truly represent aggregated individual behavior or merely a

35. Morrison (n. 2 above).

36. James R. Bettman, "A Graph Theory Approach to Comparing Consumer Information Processing Models," *Management Science,* pt. 2 (December 1971), pp. 114–28.

37. Ronald E. Frank, "Brand Choice as a Probability Process," *Journal of Business* (January 1962), pp. 43–56; and William F. Massy, "Order and Homogeneity of Family Specific Brand-Switching Processes," *Journal of Marketing Research* (February 1966), pp. 48–54.

market whose model is obtained by a complicated process. Until such verification is obtained, one should be cautious about the inferences of individual behavior which can be obtained from these models.

The large-system models vary in their aggregation techniques. Amstutz uses basically a microaddition approach. He assumes different parameters for individuals but does not use a theoretical distribution over those parameters. Farley and Ring, with their linear model, assume homogeneity; and it is not clear how Nicosia would handle aggregation. It appears microaddition would be used.

MODEL USES

There are generally three potential uses for a model: description, prediction, and understanding. Let us now turn to each group of models to determine their main area of use.

The information-processing models currently are most useful for describing and understanding *individuals* but, because of their aggregation problems, least useful for prediction in large markets. There appear to be two potential uses of such models: (1) as a basis of understanding in building better macromodels, and (2) in modeling situations where the total market consists of a very few individuals (some industrial marketing situations, for instance). Thus, information-processing models would be useful for describing the behavior of *small* groups and in furthering the development of the more macromodels. Information-processing modelers, at this point in time, do not see large-market prediction as a legitimate function for their models.

Experimental and linear models stand at the opposite end of the spectrum. In terms of a few "gross" variables, they can describe the behavior of a market or population as a whole. As mentioned above, the advantages of these models are that they can be immediately applied to the market. On the other hand, they *cannot* be used to infer any type of individual behavior. Therefore they add little to the continuing development of models. (This is not necessarily true of some of the more micro experimental and linear models such as the Fishbein-Dulany models.) They are useful for *describing* market behavior, but the modeler must be careful in any *prediction* application because of the danger of misrepresentation due to a change in the market. Without understanding, prediction in a changing environment is a hazardous undertaking.

It is uncertain to what extent stochastic models are useful. Several have been used as predictive models and have proven themselves powerful and accurate. On the other hand, because of the philosophical question raised in the previous section, of whether these are truly individual models and not merely market models, their ability to provide understanding of individuals is in question. At the level of the market, of course, they are good descriptive and predictive models.

Finally, large-system models present a similar question, although the verification of the market model is much more complicated. For example, although the Amstutz model is based upon elaborate representations of the consumer, which are then aggregated by microaddition, there has been little effort beyond face validity to verify the complex interrelations in these individual models (although Amstutz did try to verify some model components).[38] Also, it is not at all clear that the Farley and Ring and especially the Nicosia models could even be used to predict market behavior at this stage of their development. The main use of these models may be in attempting to understand behavior rather than predict it. In any case, unlike the stochastic models, at the market level it is very difficult to verify the output of the large-system models. Because verification of large-system models at both the individual *and* market levels is problematical, one must ask what these models really represent. That has not been adequately resolved to date. Certainly such a question should be considered by the potential user of such a model!

If one takes as his goal the modeling of a market (and, as we have seen, this may not necessarily be the case), it is important to determine which model fits the situation best. To a large extent this depends upon the market. If the market consists of only five consumers, it would probably be best to represent each by an information-processing model. On the other hand, one of the other techniques should be used on a market which consists of a million individuals.

In addition to the above consideration, the practitioner should realize that there are two aspects of modeling which are generally incompatible with each other—ease of use and realism. Generally, a model is able to describe a situation more realistically as it becomes more complex. Unfortunately, increased complexity implies an increased effort to estimate parameters for and obtain results from the model. On the other hand, simplistic models may not adequately represent all situations to which they are applied. Thus, the practical user must consider the realism-cost trade-off when deciding which model to use in a specific situation.

This problem is complicated further by the fact that model realism itself is hard to assess. Many models may fit the same set of data reasonably well. Also, the fact that a particular model works very well for the coffee market does not mean it will work well for the beer market. More empirical work is needed to compare model types for many product classes.[39]

We have now discussed many properties and concepts relating to formal consumer models. Table 1 attempts to summarize the basic ideas of the above sections. This overall view of the model types highlights the many contrasts and similarities.

38. Amstutz, pp. 386–93.

39. For beginnings in this area, see J. Morgan Jones, "A Comparison of Three Models of Brand Choice," *Journal of Marketing Research* (November 1970), pp. 466–73; and David B. Montgomery, "Stochastic Consumer Models: Some Comparative Results," in *Applications of Management Science in Marketing*, ed. D. B. Montgomery and G. Urban (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1970), pp. 99–113.

Table 1
Properties of Model Types

	S	IP	EL	LS: A	LS: FR	LS: Ni
World view:						
Approach to model building: philosophy (P) or structure (S)?	S	P	S	P	P&S	P
Probabilistic (P) or deterministic (D)?	P	D	P	P	P	D
Unit of analysis: individual (I) or population (P)?	P	I	P	P	P	P
General (G) or particular (P) processes?	G	P	G	G	G	G
Static (S) or dynamic (D) time frame?	D	S	S	D	S	D
Interest in process (P) or output (O)?	P	P	O	P	P	P
Data:						
Overt (O) or inner states (I)?	O	I	O&I	I	I	I
Marketing variables included?	N	Y	Y	Y	Y	Y
One-time (O) or longitudinal (L)?	L	O	O	L	L	L
Collection structured (S) or unstructured (U)?	S	U	S	S	S	S
Aggregation:						
Type of aggregation: homogeneous (H), micro-addition (M), probabilistic aggregation (P)?	P	M	H	M	H	M
Uses:						
Understanding:						
Individual?	?	Y	N	?	N	?
Market?	Y	?	N	Y	?	?
Prediction:						
Individual?	N	Y	N	?	N	?
Market?	Y	?	?	Y	?	?
Description:						
Individual?	?	Y	N	?	N	?
Market?	Y	?	Y	Y	Y	?

NOTE.—S = stochastic, IP = information processing, EL = experimental and linear, LS = large system, A = Amstutz, FR = Farley and Ring, Ni = Nicosia. N = no, Y = yes.

In the next sections, we step back somewhat and consider the future of formal models of consumer choice. We first consider how work on each of the various types can benefit research on the other model types.

INTERACTIONS BETWEEN MODEL TYPES

Findings for each of the various model types can certainly be used as input to the development of other model types. This section briefly discusses how such interactions between pairs of model types could be beneficial.

Stochastic Models and Information-Processing Models

Information-processing models can benefit stochastic models by suggesting new structures or variables with which to enrich stochastic models.[40] For example, if information-processing models suggest perceived risk of a product type as an important variable,[41] then a stochastic model might fruitfully include a perceived-risk variable which has a distribution over the population. One could then hypothesize different stochastic choice processes depending upon the particular realization of the risk variable. Another type of input from information-processing models is insight into the feedback structure of purchase events—does purchase-event feedback occur in information-processing models, and how many past purchases are involved? Finally, information-processing ideas can be useful in providing behavioral rationales for mathematical models.[42]

Stochastic models can also provide beneficial inputs to information-processing models. Of particular relevance is insight into what types of effects occur over time, since most information-processing models are static and need to be extended to take account of dynamic effects.

Stochastic Models and Linear Experimental Models

As with other interaction situations involving linear models, stochastic models can benefit from linear models if testable linear hypotheses can be proposed for stochastic models. At least one of these has already been completed by Carman (n. 2 above). In addition, the linear models may detect important variables which should be included in stochastic models. For example, a more process-oriented stochastic model might be developed from the preliminary linear model of Farley and Ring.

Stochastic Models and Large-System Models

A fascinating possibility that remains largely unexplored is to use stochastic models as components for large-system models. One could conceivably use one stochastic model—for example, a linear learning model—as a model of one population subgroup, and another model—

40. For a similar viewpoint from cognitive psychology, see Paul Slovic and Sarah Lichtenstein, "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment," *Oregon Research Institute Research Monograph*, vol. 10 (December 1970).

41. Bettman, "Information Processing Models of Consumer Behavior" (n. 6 above).

42. Private communication with Prof. A. Tversky, Stanford University, indicates work on a hierarchical elimination-choice model for which a lexicographic satisficing process rationale can be developed.

say, a Markov model—as a model of a second subgroup. Then one would aggregate not only within each subgroup but across subgroups, combining stochastic model types. This approach has not yet been tried, to our knowledge.

Information-Processing Models and Linear Experimental Models

An unresolved problem in the psychological literature is that of linear versus configural models.[43] Linear models of choice often fit well, but subjects claim they are using patterns of data, not merely linear terms. Analysis of information-processing models can help to interpret this problem and suggests that perceptual-expectations phenomena are important here.[44] Thus, information-processing models can aid in interpreting linear models.

Linear experimental models can be helpful in validating information-processing models. Process models often imply certain relations between stimuli, structural or otherwise. These relations can generate hypotheses which can be checked in a laboratory setting by an appropriate linear model. This aids in confirming information-processing microstructure which has been derived from protocols.

Information-Processing Models and Large-System Models

There is a two-way interaction that can aid both information-processing and large-system models. Analysis of information-processing models can yield generalized paradigms based on an information-processing point of view that suggest large-system models. Bettman has performed such an analysis,[45] and the general model developed bears very close resemblance to the verbal Howard-Sheth paradigm. In a similar manner, large-system models can give insights into the general structure one might expect in inferring generalized information-processing models using specific individuals' models as instances.

Linear Experimental Models and Large-System Models

Again we have a two-way general interaction. Linear models form the building blocks from which many large-system models are induced. Thus linear models can stimulate elaboration of large-system models. Also, large-system models often generate testable hypotheses that can be considered linear experimental models.

43. Louis Goldberg, "Simple Models or Simple Processes? Some Research on Clinical Judgments," *American Psychologist* (July 1968), pp. 483–96.

44. James R. Bettman, "The Structure of Consumer Choice Processes," *Journal of Marketing Research* (November 1971), pp. 465–71.

45. Ibid.

FORMAL CONSUMER-CHOICE MODELS: PROBLEMS AND PROSPECTS

Formal models of consumer choice have an intense if short history. In this section problems facing each model type are outlined, and prognoses for future progress are discussed.

Stochastic Models

The promise of stochastic models looks bright. The philosophy of modeling is sound—model the individual consumer and aggregate across consumers. However, some serious problems stand between these models and their widespread adoption.

One aspect of most of the brand-choice models in this category is that they collect all brands other than the brand of interest into a single artificial "all other" brand.[46] While, in a market of many brands, it might be reasonable to consider several similar brands as a single competitor, it seems unwise to collect *every* other brand into a single group. Fortunately, most Markov models[47] do not suffer from this problem. Also, progress is being made on alleviating this problem in other promising models.[48]

Another problem in this class of models is the lack of integration among the brand-choice, interpurchase-timing, and quantity-purchased models. Clearly if market sales are to be modeled, all three factors should be combined into a single model. Researchers have just begun to turn their attention to this problem, and it (we hope) will be resolved shortly.

A final problem with these models is that, because of their mathematical complexity, they have not included many marketing variables in their formulation. While this will continue to be a problem, new and more powerful mathematical and computational techniques should help to alleviate it in the future. As these mathematical problems are solved, it can also be expected that more micro process variables will be included.

On the positive side, stochastic models seem to provide the best prospects for modeling large-scale market behavior at the current time. It looks as though linear models are not comprehensive enough, while large-system models seem to be, at best, difficult to apply.

Information-Processing Models

As mentioned earlier, one of the major problems confronting information-processing models is the idiosyncratic nature of the models developed, due to the emphasis on depicting actual decision rules. If each

46. For example, Carman; Jones, "A Dual-Effects Model of Brand Choice"; Montgomery, "A Stochastic Response Model with Application to Brand Choice"; and Morrison (see n. 2 above).

47. Harary and Lipstein (n. 2 above).

48. Private communication with Mr. Jack Bieda, Procter and Gamble Co., Cincinnati, indicates significant progress on a multi-brand linear learning model.

individual needs a separate model, this is little consolation to the consumer-choice theorist. For the information-processing approach to be viable, some generalizations must become apparent. Thus, individual models become data points from which a more general model may be induced.

For this generalization to occur, several developments seem necessary. First, more models of individuals must be built, in more types of situations. Second, models of the same individual over time must be studied. Finally, it would be most helpful for making generalizations if methods for comparing information-processing models could be developed. One such method has been proposed, and if it proves viable, it can be used to cluster individuals and develop process-oriented typologies useful for generalization.[49]

It has been noted that building information-processing models of more individuals would be helpful in leading to generalized models. However, a second problem with information-processing models is that data collection and analysis are extremely time consuming. Methods for formalizing protocol analysis would be very helpful. Some work on such methods is underway[50] but is progressing slowly. Methods such as AID[51] that infer tree structures from data might also be tried, with the idea that inferring an information-processing model from detailed data can in fact be constructed as a complicated form of parameter estimation. Hence, developing tree structures using a formalized procedure could be thought of as a parameter-estimation technique. One would certainly need to carefully compare the estimated models with models inferred directly from the protocols to see if the idea were practical.

Finally, much work needs to be done on building learning processes into information-processing models. Most information-processing models are constructed for subjects who have *already* learned. However, using naïve foreign subjects[52] might yield data on actual learning procedures. An information-processing model of a subject playing a business game shows that such learning strategies are extremely hard to characterize.[53]

Experimental and Other Linear Models

The formulation of these models is probably not realistic of the situations being modeled, but they are easy to solve. As a result, they will undoubtedly continue to be used and may be valuable to formal consumer

49. Bettman, "A Graph Theory Approach to Comparing Consumer Information Processing Models" (n. 36 above).

50. Newell (n. 7 above); and William C. Farrell, "A Simulation Model of Decision Making in a Management Game" (M.S. thesis, Graduate School of Business Administration, University of California, Los Angeles, 1971).

51. J. Sonquist and J. Morgan, *The Detection of Interaction Effects*, Monograph 35 (Ann Arbor, Mich.: Survey Research Center, University of Michigan, 1964).

52. Jagdish N. Sheth, "How Adults Learn Brand Preferences," *Journal of Advertising Research* (September 1968), pp. 25–36.

53. Farrell.

model building, since the potential exists for pointing out additional variables which need to be included in other models.

On the other hand, the linear models seem to be too restrictive in their form to represent the market very adequately. Also, the assumption of homogeneity implicit in most linear models seems to be grossly inadequate. As a consequence, these models can probably best be used as exploratory tools to aid in formulating other, more complicated models.

Large-System Models

One problem facing the Amstutz microsimulation models, the linear realization of the Howard-Sheth model, and the Nicosia model is measurement. Extremely subtle and nontransparent constructs are involved, and developing questionnaire measures to gather data for model testing is very difficult. Farley and Ring have discussed such difficulties in the Howard-Sheth model.[54] However, psychometric techniques have made great strides in the last few years and may help with these problems.

A problem particularly inherent in simulation models such as those proposed by Amstutz is that of model validation. It is still unclear how to compare simulation results with actual results analytically, although spectral analysis has been proposed.[55] Also, estimation of parameters in simulation models has been a very hard theoretical problem.

Finally, reasonable models should be testable.[56] With broad, general models it is often hard to develop critical empirical tests that allow for model rejection. This does not seem to be so much the case for present large-system models but may cause problems with further generalizations.

Thus the main problems with large-system models are brought about by their sheer size, unwieldiness, and generality. These properties make constructs hard to specify and measure and validation difficult.

CONCLUSIONS

There are many different ways in which the various models of consumer behavior can be compared. It is important for the modeler who is engaged in this activity to be aware of these differences, since they imply quite different philosophical approaches to formal consumer models. The various types of models have been discussed within a comparative conceptual framework, in an effort to make the differences more clear to the reader.

In addition to the modeler, the practitioner also should become involved in these questions, for they have strong implications for the applicability of a particular model in a particular situation.

54. Farley and Ring (n. 19 above), pp. 435–38.

55. George Fishbein and Philip Kiviat, "The Analysis of Simulation Generated Time Series," *Management Science* (March 1967), pp. 525–57.

56. Geoffry Clarkson, *The Theory of Consumer Demand: A Critical Appraisal* (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1963).