1 MARKETING MODELS: PAST, PRESENT AND FUTURE

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We all build models all the time. When we think about how a listener is likely to respond to what we say, we are using a "model" of that person's response (which we update every time we run an "experiment"—that is, have a conversation). We link cells together in spreadsheets at the office; we draw maps to provide directions for others. Every good salesperson has a model of how a customer is likely to respond to different types of selling propositions. And every time we say, "I think that the best thing to do in that situation is X," we have used some model-based approach to determine that X was likely to be a better action than Y in that particular situation.

However, we seem to use the same word, *model*, for a variety of things. What I will try to describe is how I classify formal models in marketing. I will then identify what areas of marketing have attracted notable quantitative model building efforts in the last decade and what the achievements in those areas have been. I will close with a look ahead.

Classifying Models

Although everyone builds models all the time, some modeling is systematic and formal. I classify formal marketing models here according to their methodology and their purpose.

Methodology

There are two basic methodologies for modeling in marketing: verbal and mathematical. Verbal models, as the name suggests, are cast in prose form. Most of the models in the behavioral literature in marketing are verbal, although they may ultimately be translated into mathematical form (Figure 1). For example, Howard and Sheth's [1969] theory of consumer behavior is a verbal model of consumer behavior. Another example is Lavidge and Steiner's [1961] model of advertising: ". . . advertising should move people from awareness . . . to knowledge . . . to liking . . . to preference . . . to conviction . . . to purchase." Often, verbal models are expressed graphically for expositional reasons. Verbal models are not unique to behavioral marketing. Many of the great theories of individual, social, and societal behavior, such as those of Freud, Darwin, and Marx, are verbal models. So is Williamson's [1975] transaction-costs theory of economic behavior.

Mathematical models use symbols to denote marketing variables and express their relationships as equations or inequalities. The analysis—when correctly done—follows the rules of mathematical logic. Examples of mathematical models are Bass's [1969] model of diffusion of durables, Little's [1975] BRANDAID model, and McGuire and Staelin's [1983] model of channel structure.

Figure 1 shows a new-product growth model verbally, graphically, and mathematically.

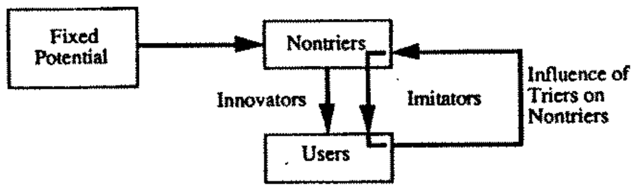
Purpose

There are essentially three purposes for modeling in marketing: measurement, decision support, and explanation or theory-building. We call the corresponding models, measurement models, decision support models, and stylized theoretical models (although it may be equally helpful to interpret these "categories" as classification dimensions for interpreting the multiple purposes of models).

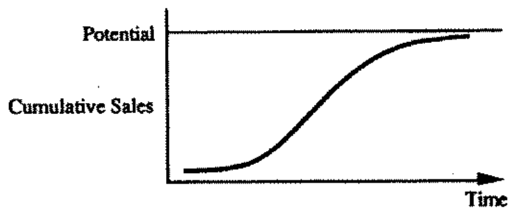
Verbal Model

New-product growth often starts slowly, until some people (early triers) become aware of the product. These early triers interact with nontriers to lead to acceleration of sales growth. Finally, as market potential is approached, growth slows down.

Graphic/Conceptual Model



(a)



(b)

Mathematical Model

$$\frac{dx}{dt} = (a + bx)(N - x)$$

where x = number of purchases by t
N = market potential
a, b = constants

(c)

Figure 1. Illustration of three model structures describing the same phenomenon.

Measurement Models

The purpose of measurement models is to measure the demand for a product as a function of various independent variables. The word *demand* here should be interpreted broadly. It is not necessarily units demanded but can be some other variable that is related to units demanded. For example, in conjoint measurement models, the demand variable is an individual's preference for a choice alternative. In Bass's [1969] model of diffusion of new durables, the demand variable is sales to first adopters

$$Q_t = \underbrace{p(\overline{Q} - N_t)}_{\substack{\text{innovation}\\ \text{effect}\\ \text{or}\\ \text{external}\\ \text{influence}}} + \underbrace{r\left(\frac{N_t}{\overline{Q}}\right)(\overline{Q} - N_t)}_{\substack{\text{imitation}\\ \text{effect}\\ \text{or}\\ \text{internal}\\ \text{influence}}} = \left(p + r\frac{N_t}{\overline{Q}}\right)(\overline{Q} - N_t)$$

where

Q_t = number of adopters at time t

$\overline{Q}$ = ultimate numbers of adopters

N_t = cumulative number of adopters to date

r = effect of each adopter on each nonadopter (coefficient of internal influence)

p = individual conversion ratio in the absence of adopters' influence (coefficient of external influence)

Figure 2a. Bass's [1969] model of innovation diffusion (in discrete time form).

$$p_k = \frac{e^{v_k}}{\sum_{j \in S_i} e^{v_j}}$$

where v_k = (deterministic) component of individual i's utility for brand k

S_i = individual i's set of brand alternatives

p_k = probability of choosing brand i

and $v_k = \sum_j b_{jk} x_{jk}$

where x_{jk} = observed value of attribute j for alternative k

and b_{jk} = utility weight of attribute j

Figure 2b. *Guadagni and Little's [1983] multinomial logit model of brand choice.*

(Figure 2a). In Guadagni and Little's [1983] model, the dependent variable is the probability that an individual will purchase a given brand on a given purchase occasion (Figure 2b).

The independent variables in measurement models are usually marketing mix variables—again interpreted broadly to mean any variables the firm controls—but they could include variables to account for seasonality, consumer characteristics, and competitors' actions. In conjoint measurement models, for example, the independent variables are usually the attributes of the choice alternatives. Bass's model has two independent variables, cumulative sales since introduction and the square of cumulative sales since introduction. Guadagni and Little's model has several independent variables, including whether or not the brand was offered on deal at a given purchase occasion, regular price of the brand, deal price (if any), and brand loyalty of the individual. These examples suggest that measurement models can deal with individual (disaggregate) demand or aggregate (market-level) demand.

Once the demand functions have been specified, they are then calibrated to measure the parameters of the function. Calibration reveals the role of various independent variables in determining demand for this product: which variables are important and which are unimportant. Also, once the demand function has been calibrated, it can be used to predict demand in a given situation by plugging in the values of the independent variables in that situation. A variety of methods are used to calibrate demand functions: judgment, econometric techniques, experimentation, simulation, and so forth. For example, Bass uses multiple regression to calibrate his model; Srinivasan and Shocker [1973] use linear programming to calibrate their conjoint model; Guadagni and Little use maximum-likelihood methods.

Measurement models can advance as data or measures improve (scanner data, for example) or better calibration methods and procedures become available (maximum likelihood methods for generalized logit models, for example). The fine book by Hanssens, Parsons and Shultz [1990] deals almost exclusively with measurement models.

Decision Support Models

Decision support models are designed to help marketing managers make decisions. They incorporate measurement models as building blocks but go beyond measurement models in recommending marketing-mix decisions for the manager. The methods used to derive the optimal decision vary across applications. Typical techniques are differential calculus; operations research techniques, such as linear and integer programming; and simulation. Little and Lodish's [1969] MEDIAC model for developing media schedules is an example. They developed an underlying measurement model, relating sales in each segment to the level of advertising exposure. That model is calibrated by managerial judgment. The estimated sales-response function is then maximized to develop an optimal media schedule using a variety of maximization techniques—dynamic programming, piecewise linear programming, heuristic methods—and incorporating various technical and budgetary constraints.

Figure 3 shows a decision support system. The measurement module, centered on models of the workings of the marketplace takes input from the marketer, from the environment, and from competition, producing a

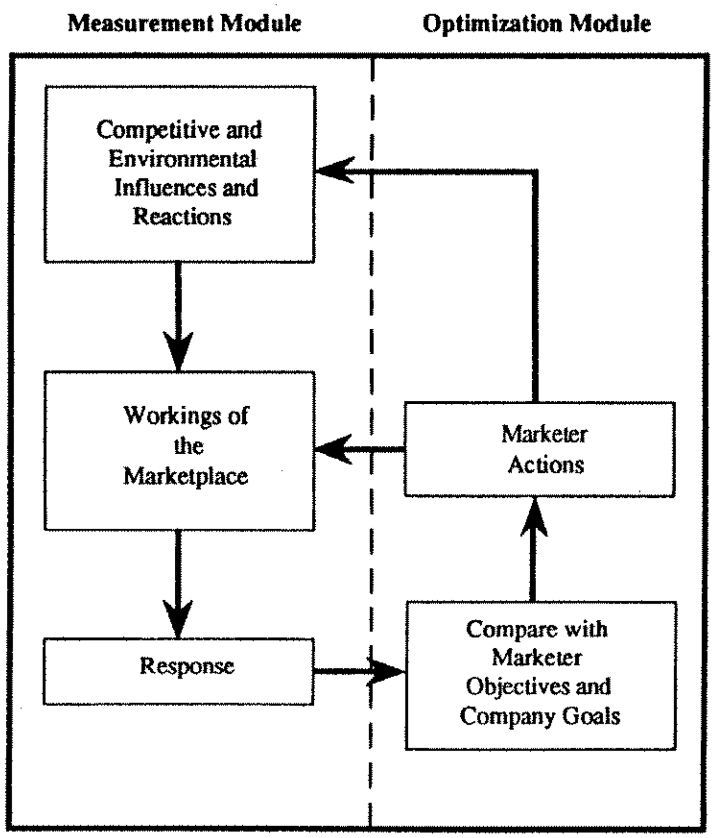


Figure 3. A decision support system, showing measurement and optimization modules.

response. That response, compared with the marketer's objectives, leads to a new round of marketer actions. The arrow leading from "marketer actions" to "competitive reactions" recognizes the fact that, unlike other environmental variables, competitors' actions could be affected by "our" actions.

Stylized Theoretical Models

The purpose of stylized theoretical models in marketing is to explain stylized marketing phenomena: A stylized theoretical model makes a set of assumptions that describes a hypothesized marketing environment. Some of these assumptions will be purely mathematical, designed to make the analysis tractable. Others will be substantive assumptions with intended empirical content. They can describe such things as who the actors are, how many of them there are, what they care about, the external conditions under which they make decisions, and what their decisions are about. These latter assumptions participate in the explanation being offered. The concept of a model in stylized theoretical modeling is different from the concept of a decision support model. There a model is defined as a mathematical description of how something works. Here it is simply a setting—a subset of the real-world—in which the action takes place. A stylized theoretical model attempts to capture the essence of a situation, usually at the cost of fidelity to its details.

Once a model has been built, the model builder analyzes its *logical* implications for the phenomenon being explained. Then another model, substantively different from the first, is built—very likely by another model builder—and its implications are analyzed. The process may continue with a third and a fourth model, if necessary, until all the ramifications of the explanation being proposed have been examined. By comparing the implications of one model with those of another, and by tracing the differences to the different assumptions in the various models, we can develop a theory about the phenomena in question (Figure 4) This is as if a logical experiment were being run, with the various models as the "treatments." The key difference from empirical experiments is this: in empirical experiments the subjects produce the effects; here the model builder produces the effects by logical argument and analysis.

As an example consider Figure 5, where two key variables driving the design of optimal salesforce compensation plans are displayed: salesperson attitude toward risk and observability of salesperson effort. In Model 1, the simplest model, where the salesperson is risk neutral and effort is

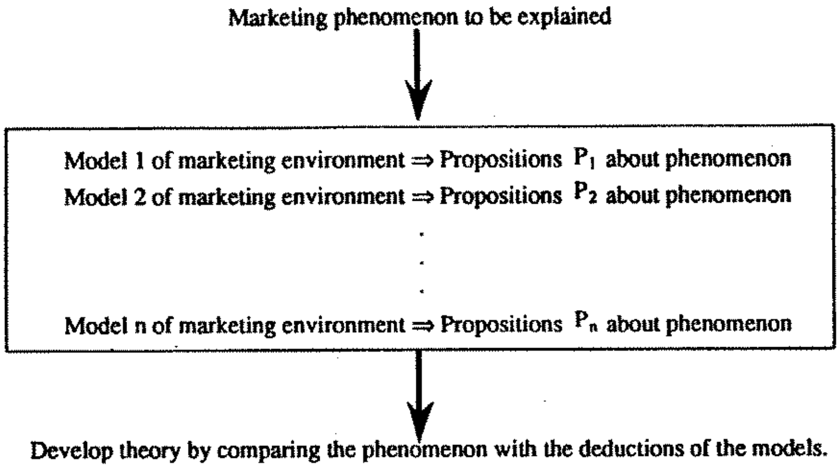


Figure 4. Overview of the stylized theoretical modeling process.

observable, any combination of salary (certain) and commission (risky) will be equally attractive to the risk-neutral salesperson. In contrast, in Model 3, where the salesperson's effort is unobservable, a pure commission scheme (based on gross margin) induces the salesperson to work in the firm's best interest (while maximizing his income) [Farley 1964]. With risk averse salespeople and unobservable effort (Model 4), under some technical conditions, the optimal compensation scheme involves both salary and commission [Basu et al. 1985; Grossman and Hart 1983].

Figure 5 looks like a 2×2 experimental design with two factors and two levels of each factor. Comparing model 1 versus 2 and model 3 versus 4 shows that risk preference has a "main effect" on the optimal compensation plan: with risk neutrality, salaries are not needed; with risk aversion, commissions are not needed. One sees similar main effects on the need for commissions with observability. Interactions appear as well. (Coughlan [1994] discusses the salesforce compensation literature in more detail.)

The main purpose of stylized theoretical modeling is pedagogy—teaching us how the real world operates—and that purpose is sometimes well served by internally valid theoretical experiments. But what about the practical use of such work for marketing managers? Such models are of direct value to managers when they uncover robust results that are independent of the unobservable features of the decision-making environment. Under these circumstances, the models have two uses: (1) as direct qualitative guidance for policy ("in our situation, we need low (high) proportions of salesforce compensation in commissions") and (2) as the

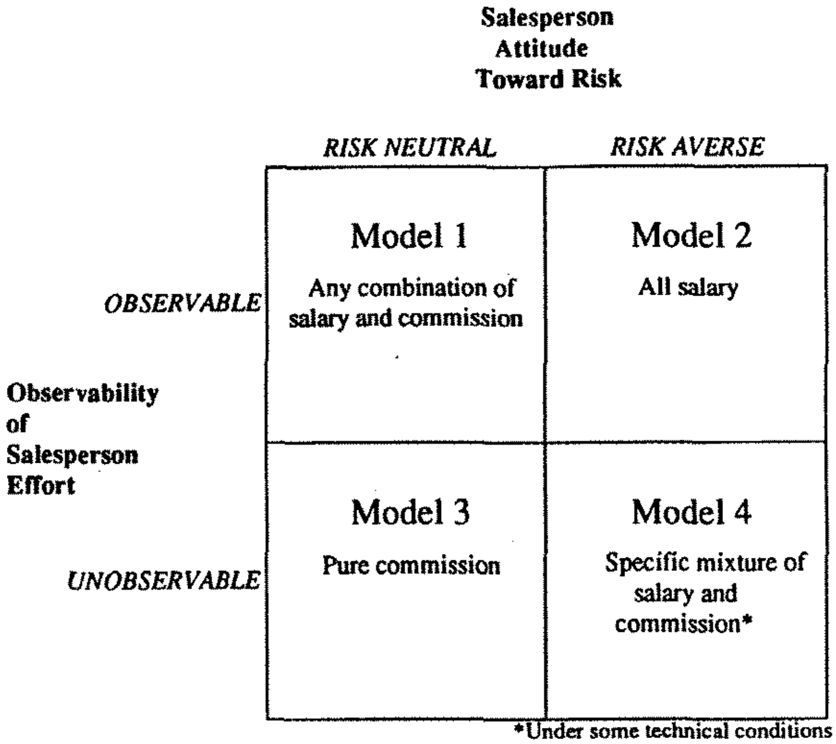


Figure 5. The experimental design for stylized theoretical models for optimal salesforce compensation. Different model builders have provided the results in different cells of the matrix.

basis for specifying operational models and associated decision support systems that can adapt the theory to a particular environment and generate quantitative prescriptions. For example, Mantrala, Sinha and Zoltners [1990] develop a decision support system that extracts a salesperson's utility function (via conjoint analysis). Their DSS then suggests a compensation plan for the salesperson that maximizes the firm's profit. They illustrate their system with an example showing nearly a 10 percent increase in firm profits associated with use of the results from the DSS.

Validating Marketing Models

For a model in any of these broad categories to contribute to marketing knowledge or to marketing practice, it must be validated. What validation criteria are appropriate will differ by category.

Broadly speaking, four main criteria for validation are relevant for marketing models: measure reliability and validity, face validity, statistical validity, and use validity [Coates, Finlay, and Wilson 1991; and Naert and Leeflang 1978, Ch. 12].

A model cannot be valid in an overall sense if the variables included in the model are not measured in a valid way. *Measure validity* is the extent to which an instrument measures what it is supposed to measure. A measure with low validity has little value. However, even if a measure is valid, it may not be possible to measure it without error. *Measure reliability* is the extent to which a measure is error-free.

Measure validity has two parts: convergent and discriminant validity. *Convergent validity* is the extent to which an instrument correlates highly with other measures of the variable of interest; *discriminant validity* is the extent to which an instrument shows low correlation with other instruments supposedly measuring other variables.

Face validity is the reductio ad absurdum principle in mathematics, which shows the falsity of an assumption by deriving from it a manifest absurdity. The idea is to question whether the model's structure and its output are believable. Face validity is based on theory, common sense, and known empirical facts (experience). Massy [1971] describes four areas for face validity: model structure, estimation, information contribution, and interpretation of results.

The validity of the model structure means that the model should do sensible things. Sales should be nonnegative and have a finite upper bound. Market shares should sum to one. Sales response to advertising spending might account for decreasing returns or first increasing and then decreasing returns to scale.

The choice of *estimation method* is another essential aspect of face validity. For example, if a reasonable set of assumptions about the process generating the data (or previous studies) suggests that residuals are autocorrelated, then the use of ordinary least squares is inappropriate and generalized least squares may be the appropriate and valid estimation procedure.

The amount of information contributed by the model also dictates its value as well as its validity. For example, promotional-response models can be calibrated before, during and after the promotional period to assess their impact. If model parameter estimates are not statistically significant, the model is of limited value in assessing promotional impact, and different measures or models may be required.

Finally, the level and interpretation of results affect model implementability and validity in much the same way that model structure does. If the price or advertising elasticity of demand has the wrong logical sign, the model loses validity and hence implementability.

Another criterion for validing marketing models is statistical validity, the criterion employed to evaluate the quality of a relationship estimated by econometric methods. The important issues in a marketing context usually relate to goodness of fit and the reliability of the estimated coefficients, multicollinearity, and assumptions about the disturbance term (homoscedasticity and autocorrelation).

Validation also relates to the intended use of the model. Validity for descriptive models places heavy requirements on face validity and goodness of fit. For a normative model, the reliability of a model's response coefficients, those that enter into policy calculations, would seem most critical. For predictive validity, a goodness-of-fit measure, such as R^2 or mean-squared deviation, is often used on a holdout or validation sample. The use of such a sample makes the validation task predictive, while measuring goodness of fit on the estimation data gives information useful only for descriptive validity.

Most econometric studies include two sets of validity tests. The first set deals with checking the model's assumptions for problems, such as multicollinearity, autocorrelation, nonnormality, and the like. This task is called specification-error analysis. If no violations are identified, the model as a whole can be tested and, most important, discrimination tests between alternative models can be performed [Parsons and Schultz 1976, Ch. 5].

For measurement models, measure validity, face validity and statistical validity are most critical. For decision support systems models, all criteria are important, but use-validity is most critical. For stylized theoretical models, the model-structure component of face validity is most relevant. Indeed, as stylized theoretical models deal with mostly very simplified marketing situations, measurement validity, estimation validity, and statistical validity are largely meaningless [Moorthy, 1990], although in the long run, those models (or their advocates) must be held accountable for their external validity when their results are used in practical settings.

Trends in Marketing Models

Developments in science can proceed from advances in any one of several dimensions: *theory* (the general theory of relativity replaced Newton's law of gravitation); *data* (the human genome project is amassing data to map the workings of human genetic structure) and *technology/methodology*

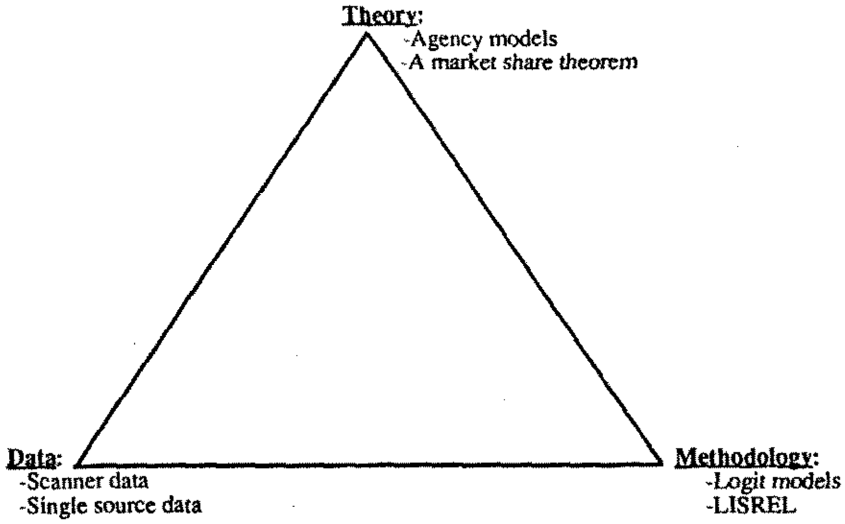


Figure 6. The scientific triad: advances in marketing science can emerge from any vertex.

(telescopes have unearthed the mysteries of the large; microscopes of the small). So it is in marketing. As Figure 6 suggests, we have seen significant advances in all three areas that have changed the focus of developments of marketing models. (Stylized theoretical models focus on advances in theory, measurement models on advances in data and methodology, and decision support models, which integrate all three vertices, rely on advances of any type.)

We all have different impressions about what issues are topical and where the frontiers are in any field. What follows is my personal impression.

(1) Marketing models are having a strong effect on both academic developments in marketing and marketing practice. During the 1980s, two new and important journals were started: *Marketing Science* and the *International Journal of Research in Marketing* (*IJRM*). Both are healthy, popular, and extremely influential, especially among academics. And both reflect the developments of marketing models. In addition, on the practice side from 1980 to 1990, the Edelman Prize Competition (held annually to select the best example of the practice of management science) selected seven finalists in the field of marketing and two winners [Gensch, Aversa, and Moore 1990; and Lodish et al. 1988).

(2) New data sources are having a major impact on developments in modeling markets. One of the most influential developments in the 1980s has been the impact of scanner data. Typically two or more special sessions at national meetings concern the use of scanner data, a special interest conference on the topic was held recently, and a special issue of *IJRM* was devoted to the topic. Scanner data and the closely related single source data (where communication consumption data are tied into diary panel data collected by means of scanners) have enabled marketing scientists to develop and test models with much more precision than ever before. Indeed, the volume of the data has forced researchers to develop new tools to make sense out of the explosive volume of the data [Schmitz, Armstrong, and Little 1990].

(3) Theoretical modeling has become a mainstream research tradition in marketing. While the field of microeconomics has always had a major influence on the development of quantitative models in marketing, that influence became more profound in the 1980s. The July 1980 issue of the *Journal of Business* reported on the proceedings of a conference on the "Interface between Marketing and Economics." In January 1987, the European Institute for Advanced Studies in Management held a conference on the same topic and reported that ". . . the links between the two disciplines were indeed strengthening" [Bultez 1988]. Key papers from that conference were published in the fourth issue of the 1988 volume of *IJRM*. Issues 2 and 3 of the 1990 volume of *IJRM* on salesforce management provide several examples of how agency theory (a microeconomic development) is being used to study salesforce compensation. Other major theoretical modeling developments, primarily in the areas of pricing, consumer behavior, product policy, promotions, and channels decisions, are covered in detail in Lilien, Kotler, and Moorthy [1992].

(4) New tools and methods are changing the content of marketing models. The November 1982 issue of the *Journal of Marketing Research* was devoted to causal modeling. A relatively new methodology at the time, causal modeling has become a mainstream approach for developing explanatory models of behavioral phenomena in marketing. As the August 1985 special issue of *JMR* on competition in marketing pointed out, such techniques as game theory, control theory, and market share/response models are essential elements of the marketing modeler's tool kit. And finally, the explosion of interest in artificial intelligence and expert systems approaches to complement traditional marketing modeling approaches has the potential to change the norms and paradigms in the field. (See the April 1991 special issue of *IJRM* on expert systems in marketing, and Rangaswamy [1994].)

(5) Competition and interaction is the key marketing models game today. The saturation of markets and the economic fights for survival in a world of relatively fixed potential and resources has changed the focus of interest in marketing models, probably forever. A key-word search of the 1989 and 1990 volumes of *Marketing Science*, *JMR*, and *Management Science* (marketing articles only) reveals multiple entries for *competition*, *competitive strategy*, *noncooperative*, *games*, *competitive entry*, *late entry*, and *market structure*. These terms are largely missing in a comparable analysis of the 1969 and 1970 volumes of *JMR*, *Management Science*, and *Operations Research* (which dropped its marketing section when *Marketing Science* was introduced but was a key vehicle for marketing models papers at that time).

Marketing Models in the 1990s

Marketing models have changed the practice of marketing and have helped us to understand the nature of marketing phenomena. That trend will continue—the area is healthy and growing. Most of us are better extrapolators than visionaries—we are able to perceive extensions of the status quo rather than paradigm shifts. I am not a paradigm shift forecaster, but let me take a crack at a few extrapolations that I think will have a dramatic impact on developments in marketing models in the next decade.

(1) Interface Modeling. Marketing is a boundary-spanning function, linking the selling organization with buyers and channel intermediaries in some way. To operate most effectively, its activities must be coordinated with other functional areas of the firm. Two areas that have begun to see research are the marketing-manufacturing interface (see Eliashberg and Steinberg [1994] for a review) and the marketing-R&D interface (see Griffin and Hauser [1992] for a review). In both these cases, the firm is suboptimizing by looking at the marketing function, given an R&D manufacturing decision; by coordinating efforts of several functions, firms can make savings in many situations. I expect these areas to be explored both theoretically and empirically in the next decade.

(2) Process Modeling. Models of competition and models of bargaining and negotiations have generally focused on identifying equilibrium outcomes. Yet markets rarely reach such equilibria; indeed, even the equilibria that are obtainable are often determined by the "transient" part of the analysis. I expect that models of nonequilibrium relationships will be built

and tested [Balakrishnan and Eliashberg 1990]. Those tests will become more do-able given the ability of interactive computer networks to capture the dynamics of moves and countermoves in negotiations, for example.

(3) Models of Competition and Coordination. The markets of the 1990s will be characterized by what I term strategic competition. What I mean by that is that our models will find those situations (like the tit-for-tat solution to repeated prisoner's dilemma games that induces cooperation [Axelrod 1984; and Fader and Hauser 1988]) that encourage price coordination in low margin markets, that allow for mutual "understandings" about permitting monopolies or near monopolies in small market niches and the like. This is in contrast to most of our current models of competition that focus on the "warfare" aspects of competition (what game theorists refer to as mutual best response).

(4) Marketing Generalizations. Meta-analysis, or what Farley and Lehmann [1986] describe as "generalization of response models," must become the norm for the development of operational market response models in the 1990s. It is absurd to analyze data on sales response to price fluctuations, for example, and ignore the hundreds of studies that have previously reported price elasticities. The 1990s will see such "generalizations" become formal Bayesian priors in estimating response elasticities in marketing models. Grouping our knowledge in this way will allow the discipline to make direct use of the information that it has been accumulating.

(5) New Technologies. Single source data will boost our ability to tie advertising and communications variables into consumer choice models. The increasing and expanding use of electronic forms of communications, data entry, order entry, expanded bar coding, and the like will provide explosions of data that will stimulate the development of marketing models parallel to those that resulted from the introduction of scanner data. For example, it is feasible for an airline reservation system to capture the complete set of computer screen protocols facing a travel agent when making a client's booking. Since the actual booking (the airline connection chosen, for example) is eventually known, an airline can test the impact of different ways of presenting alternatives to the travel agent (time order, price order, alphabetical order within a time-window for departure specified by the client) on both the travel agent's search process (the computer screen options the agent selects), and the final choice. The implications of such technology for model development, experimentation, and testing are enormous.

(6) New Methodologies. Logit and related choice models had a great

effect on both the development of marketing models and their application in the 1980s. (For a striking example of the effect such modeling had at one firm, resulting in an application that won the 1989 Edelman Prize, see Gensch, Aversa, and Moore [1990].) I see Bayesian procedures having a similar effect in calibrating marketing models in the 1990s. Most marketing analysts still estimate model parameters and elasticities classically, as if no prior guidance is available from past studies or no relationship exists to other, parallel studies in similar markets. Bayesian methods require more thought (education) and more computation. As marketing scientists, we must deal with the pedagogic issue. Advances in computation will increasingly allow analysts to exploit coefficient similarity across equations relying on similar data (perhaps from different regions or different market segments) to produce more robust estimates—so called shrinkage estimation (see Blattberg and George [1991] for a marketing illustration).

(7) Intelligent Marketing Systems. The 1970s and early 1980s saw the explosion of decision support systems (DSS) in marketing [Little 1979]. A DSS can be very powerful, but used inappropriately, it can provide results that are either worthless or, possibly, foolish. The 1990s will see the development of a generation of IMSs (Intelligent Marketing Systems) that will have "autopilots" on board the marketing aircraft (the DSS) to take care of routine activities and focus the analyst's attention on outliers. Forerunners of such systems are Collopy and Armstrong's [1989, 1992] rule-based forecasting procedure and Schmitz, Armstrong and Little's [1990] CoverStory system. Collopy and Armstrong's system relies on a review of published literature on empirical forecasting as well as knowledge from five leading experts to form an "expert base." The system then provides rules for cleaning and adjusting the raw data, rules for selecting an appropriate set of forecasting models, and rules for blending the models. CoverStory uses rules that experienced sales promotion analysts employ to clean, summarize, and "scan" scanner data to summarize what has happened in the most recent set of data and to identify the key points that are hidden in data summaries and reports. Indeed, the system even writes the managerial cover memo—hence the name.

(8) More Impact on Practice. Even several decades after the earliest operational marketing models were introduced, their impact on practice remains far below its potential. Shorter life cycles, more competitive (and risky) decisions, better theory, faster computers, new technologies, and the convergence of new developments will permit marketing models to affect marketing practice almost as profoundly as they have the academic realm.

This last point—the impact on practice—merits further discussion. Few topics concern marketing modeling practitioners and academics alike as much as the low level of impact new developments have on practice. I see at least three reasons for this situation: expectations, transfer dysfunction, and model quality.

Expectations for new marketing models are very much akin to expectations for new products of any type: most fail in the marketplace, but their developers always have high expectations for them, or they wouldn't invest in their development in the first place. The broad successes in the fields of pre-test market models (Urban and Katz [1983], for example) and in conjoint analysis [Wittink and Cattin 1989] demonstrate that models that directly solve problems that occur similarly across organizations and product-classes have great value. The domain of profitable application of such models is limited, however, and we should not expect to see the same levels of success in such areas as strategy and competitive analysis, where the models may be more valuable in guiding thinking than in providing definitive recommendations for action. As with any program to develop a new product, we must tolerate a high rate of failure in the marketplace as a cost associated with innovation.

Transfer dysfunction frustrates academics and practitioners alike. Few academic marketing modelers have the personal characteristics associated with successful implementation. Hence, much good work with potential great practical value lies in our academic literature like "better mousetraps" waiting for eager customers. The academic model-developers do not have the skills to sell and implement their models, and we have not developed a set of appropriately trained transfer agents.

Finally, many of the models in our literature (and many in academic research in general) are trivial or misguided. Models published on research questions many generations removed from real problems (if ever stimulated by real problems in the first place) are not likely to affect practice. As a field, marketing modelers are not alone here; however, we do have to share in the academic blame associated with the irrelevance of much of our work.

But I will not dwell on unfulfilled expectations and shortcomings; I leave such angst to others. Our glass is half full, after all, and the successes I have outlined here are substantial.

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Note

Parts of this paper are drawn from Lilien, Kotler and Moorthy [1992].

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