Building Models for Marketing Decisions: Past, Present and Future

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Abstract

We review five eras of model building in marketing, with special emphasis on the fourth and the fifth eras, the present and the future. At many firms managers now routinely use model-based results for marketing decisions. Given an increasing number of successful applications, the demand for models that are suitable in other contexts, will accelerate. At the same time the development of innovative modeling approaches pushes the practical use of models in new areas. The latter is especially critical in an environment that changes rapidly. We propose a perspective on the "new marketing" and suggest some contributions models can make in the twenty-first century.

Keywords: Models; Implementation; Model-building process; New marketing

1. Introduction

A historical perspective suggests the following five eras of model building in marketing.[1]

a. An era characterized by the direct application of existing operations research (OR) and management science (MS) methods to marketing problems: 1950-1965.
b. An era characterized by the adaptation of models to fit marketing problems. These larger and more complete models capture marketplace reality better but they lack simplicity: 1965-1970.
c. In the era of implementable models there is an increased emphasis on models that are acceptable representations of reality and are easy to use: 1970-1985.
d. In the fourth era models are increasingly implemented, and there is an interest in marketing decision support systems. In this era we also see an increase in routinized model applications which results in meta-analyses and studies of the generalizability of results: 1985-2000.
e. Changes in technology stimulate the growth of new exchange systems, and there is an opportunity and a need for new modeling approaches: 2000- .

We describe the first three eras in Section 2. In Section 3, we discuss the fourth era, the present status of marketing models, where we also provide examples of marketing decisions for which model-based automation is appropriate, and we discuss the use of existing models to new application areas. We argue that modeling can be successfully completed based on a systematic process. We describe the individual stages in this process and we discuss some recent developments pertaining to these parts. In Section 4 we suggest new modeling approaches to accommodate the latest strategic thinking. Primarily due to technological developments, the future will allow consumers to maximize customized utility functions effectively and efficiently. We propose that consumers will explicate multidimensional utility functions, that they will utilize customized support called infobots to choose products and services and to bid prices, and that suppliers will use public and private data sources to change customized offerings over time.

[1] See also Leeflang et al. (2000). Definitions of the first three eras are due to Montgomery (1973) and Eliashberg and Lilien (1993). It should be clear that we do not imply the existence of natural boundaries between these eras.

2. The past

We briefly review the characteristics of the first three eras:

2.1 Transposition of OR/MS-methods: 1950-1965

The first era is defined primarily by the transposition of OR/MS methods into a marketing framework. OR and MS largely emerged during and after World War II with algorithms and processes applicable to production and logistics. Successes in those areas encouraged researchers in the early 1960's to solve problems in other areas such as finance and marketing.

Initially, the emphasis was on the application of existing OR/MS methods for the solution of specific problems. The OR/MS tools include mathematical programming, computer simulations, stochastic models (of consumer choice behavior) and dynamic modeling. Difference and differential equations, usually of the first order, were used to model dynamics. The methods were typically not realistic, and the practical usefulness of these methods in marketing applications was therefore limited.

A relatively large number of models was developed in this era. They are classified, according to primary purpose or intended use, as descriptive, predictive and normative models. Descriptive models describe decision or other processes (Cyert and March, 1963). An important subset is the set of stochastic consumer behavior models such as purchase incidence, purchase timing and brand choice models. Purchase incidence models are due to Ehrenberg (1959, 1972, 1988) and Chatfield et al. (1966). A key property in these models is the Poisson process, which has the property that the distribution of the number of units purchased in any interval depends on its length. Purchase timing models are closely related to purchase incidence models. They specify the probability that the waiting time between successive purchases is no more than some specified value. Markov models (Maffei, 1960; Harary and Lipstein, 1962; Telser, 1962) and learning models (Kuehn, 1961, 1962; Herniter and Howard, 1964) are well-known examples of brand choice models.

Although virtually all models can be used for predictive purposes, a purely predictive model lacks *the explanatory variables* that provide *conditional* predictions. For example, a model of sales based on time series observations may provide accurate predictions if the systematic patterns in past data also apply to the future. An attractive early example of such a predictive model is due to Fourt and Woodlock (1960). They propose that new-product sales can be predicted from early data about the percent of consumers trying the product and the percent of consumers repeating. The ultimate trial rate (penetration) is estimated by assuming exponential growth, where the repeat purchase rate on the $(n+1)^{th}$ purchase occasion is a function of the rate on the n^{th} occasion.

Normative models have, as one of their outputs, a recommended course of action. Dorfman and Steiner (1954) derived a theorem which specifies the optimal values of price, advertising and quality for profit maximization. This model has been modified and extended in many directions (Ferber and Verdoorn, 1962; Lambin, 1970). Other models optimize an objective function simultaneously for multiple brands where the optimal value of marketing instruments are obtained from algorithms developed in game theory (Friedman, 1958; Shubik, 1959; Shakun, 1965, 1966).

We note that many models have multiple purposes. Vidale and Wolfe (1957) propose a model of sales as a function of advertising expenditures which can serve as both a descriptive and a predictive model. The model is empirically based, and it is used to describe the effect of a constant advertising expenditure during some period. This description is used for (conditional) predictions of a pulse campaign. By adding cost- and profit functions to the estimated demand function, Vidale and Wolfe obtain normative implications. Magee (1953) uses a Poisson distribution for the number of units sold to a given retailer during a specific period. The effects of promotional efforts are considered by comparing the sales probability distributions of retailers exposed to promotional activity (the top 40 percent based on previous sales) with the sales probability distribution of other retailers. The resulting estimates are used by Magee to determine the optimal allocation of promotional efforts to the retailers.

It is noteworthy that in this era many models were developed for consumer durables (such as automobiles) and industrial products. Industrial marketing applications include sales force allocation models (Brown et al., 1956) and competitive bidding models (Edelman, 1965).

This period also includes the introduction of econometric methods into marketing for the estimation of demand relationships. The econometric applications, however, were hampered by the limited availability of relevant data. Thus, the early applications of econometrics in marketing have to be seen more as treatises on the possible use of methods for addressing marketing problems than as research providing useful substantive results.

2.2 Models that fit marketing problems: 1965-1970

The second era can be characterized by the adaptation of models to fit marketing problems. Researchers felt that lack of realism was the principal reason for the dearth of implementation of the early marketing models. The resulting models are more representative of reality, but they often lack simplicity and usability. In this era, the descriptive models of marketing decision making include work by Howard and Morgenroth (1968). Their model describes pricing decisions made by managers in a large firm operating in an oligopolistic market. The model was developed because the procedures were considered too complex for traditional communication purposes. Howard and Morgenroth interviewed the pricing decision makers to obtain a fairly simple descriptive model.

A predictive model that received enormous attention by academics and practitioners alike is the new-product growth model developed by Bass (1969). Bass proposes that category sales of a new durable, assuming at most one unit purchased per customer, depends on innovators and imitators. Based on a few simple assumptions about the probability of an initial purchase as a function of the number of previous purchases (by others) he derived an expression for category sales as a quadratic function of cumulative (initial) purchases. He showed that the estimated parameters from the early years of sales can provide excellent forecasts of the amount of peak sales and the timing of the peak. The Bass' model has been applied numerous times and it has been extended to include, among other things, the effects of marketing variables.

Examples of applications of advanced econometric methods attracting research attention can be found in Lee et al. (1970) and Massy et al. (1970). Separate models were created to deal with specific marketing problems such as models for product decisions, for pricing decisions, for sales force decisions, etc. (see Montgomery and Urban (1969) and Kotler (1971) for illustrative state-of the-art books). In a critical evaluation of the literature, Leeflang (1974) nevertheless argued that many of those models failed to represent reality. For example, many models failed to consider the effects of competition, were static and only considered one marketing instrument.

2.3 Implementable marketing models: 1970-1985

In the third era there is increased emphasis on models that are acceptable representations of reality, and at the same time are easy to use. Thus the focus shifts from "isolated" decision problems to implementation and implementability.

Pioneering work on the implementation issue is provided by Little (1970) on the concept of a decision calculus. He examines the question of why models are not used, and he suggests the following possible answers:

- good models are hard to find;
- good parameterization is even harder;
- managers do not understand models;
- most models are incomplete.

Little also prescribes remedial action. He states that a manager needs a decision calculus, i.e. a model-based set of procedures through which the manager can bring data and judgments to bear on the decisions at hand. He proposes criteria which a model must satisfy in order for it to be labeled a decision calculus model. These criteria are related to model structure, to ease of use and to implementation strategy. With respect to model structure, Little suggests that models should be simple, complete on important issues, adaptive and robust. Robustness applies to a model if it is difficult for a user to obtain bad answers. Robustness can be achieved with a structure that constrains answers to a meaningful range of values. Also, if the actual values of a criterion variable are constrained (such as market shares which sum to one, and are bounded by zero and one), the model counterpart should satisfy the same constraints. Such models are called logically consistent. In this era much attention focussed on the specification of logically consistent market share models such as MCI- and MNL-models (Nakanishi and Cooper, 1974, 1982; Cooper and Nakanishi, 1988). Many researchers have compared the predictive performance of (non-robust) linear and multiplicative market share models and (robust) attraction models (Naert and Weverbergh, 1981, 1985; Brodie and de Kluyver, 1984; Ghosh et al., 1984; Leeflang and Reuyl, 1984). The results show that the attraction models do not always have significantly greater predictive power than their non-robust counterparts. This may be due to specification problems such as omitted variables, functional form and aggregation.

A productive implementation strategy is modular model building. Modularity means that the end result is obtained by putting together a set of submodels or modules. For example, Little's (1975) BRANDAID marketing mix model has a set of modules, one for each marketing instrument. If a user does not plan to use, say, promotional activities, the promotion module is not included in the model. However, if the user decides that promotion should be part of the marketing mix in a subsequent period, the promotion module can be added to the existing structure. The modular approach makes it easier for a user to understand how the model works and it provides the user with flexibility. These advantages will facilitate adoption and use (implementation) of a model.

In this era we also see the introduction of models parameterized with subjective (as well as objective) data. If data are lacking or the available data have insufficient quality, a model that captures a decision maker's judgments about outcomes under a variety of conditions can be helpful. Such a "model of man" (model of judgments) can provide the basis for superior decisions in future time periods relative to the decision maker's judgments on which the model is based (see Mitchell et al., 1991).

Other developments include strategic marketing (planning) models[2] and Marketing Decision Support Systems (MDSS). Other research focuses on relations between marketing models and organizational design, and between marketing decisions and issues in production and logistics. Importantly, due to Little, this is an era in which researchers attempt to specify implementable marketing models. This period also witnesses the introduction of the multinomial logit model in the "marketing science" literature through the pioneering brand choice research of Guadagni and Little (1983).

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[2] For a survey and an in-depth discussion see Wind and Lilien (1993).

The increasing availability of data offers opportunities for researchers to build models that advance our marketing knowledge and produce generalizable phenomena. This development was stimulated by an organized stream of research. Based on the success of the *Market Measurement and Analysis* conference at Stanford in 1979 (Montgomery and Wittink, 1980), there have been annual *Marketing Science Conferences*. These conferences provided financial support for and stimulated the founding of the *Marketing Science* journal in 1982, which has facilitated substantial growth in quantitative, analytical and empirical treatments of marketing phenomena. Another important stimulus in this era is the launch of the first issue of the *International Journal of Research in Marketing*, the official journal of the European Marketing Academy, in 1984. We discuss selected research appearing especially in various special issues of *IJRM* in Section 3.

3. The present

3.1 Maturity

The present era represents a level of *maturity* in model building for marketing decisions. This maturity is reflected in the following aspects.

a. Some models have been applied many times in a somewhat *standardized form*. Wide applicability of a given model would not be possible without the availability of detailed data sets for many products, access to appropriate software and estimation methods, and sophistication on the part of both the model builder and the model user. Of course, a given model would not be applied across many data sets if the model results were of no use to the decision maker.
b. There is a recognition of opportunities for model-based automation of market decisions (Section 3.2).
c. The publication of empirical studies completed by different researchers who use different models and different data sets has facilitated the examination of similarities and differences between substantive findings. This has led to meta-analyses and empirical generalizations (see also Section 3.3).
d. Existing models developed in one context are applied, and adopted if necessary, to new contexts (Section 3.4).

All of these activities are the hallmark of a mature industry. At the same time, there is a plethora of published empirical results pertaining to a wide variety of marketing issues which has contributed to the further development and adaptation of quantitative methods (Wansbeek and Wedel, 1999).

The maturity of model building and usage has actually come about in a short time. One reason for the rapid acceptance of model-based results is the experience gained by the marketing research community during the first three eras. Another reason is the introduction of new Business-to-Business (B2B) services such as IRI's BehaviorScan in the mid 1980's. BehaviorScan offers the attractive feature that clients can manipulate one or more marketing variables by allocating households randomly to different treatment conditions in a field experiment. This allocation process is flexible and fast through the cooperation of local cable companies. Purchase measurement takes place by having households use plastic ID cards in all relevant outlets, which are equipped with scanners. This unique setup provides clients the opportunity to improve decisions about (television) advertising content and weight (frequency) for new and established products, controlling for other marketing activities (and sometimes manipulating other variables as well).

As the penetration of scanners across supermarkets and other retail outlets increased, IRI and ACNielsen saw the opportunity to provide more frequent, more detailed, and more accurate tracking services than had been available from Nielsen's bimonthly measures.[3] Until the advent of scanner data, Nielsen's mantra was that it reported the score (market share, relative price, etc.) very accurately but it would not predict nor explain the score. In the new environment this became an untenable position for several reasons. One is that clients became interested in understanding the effects of marketing activities on sales or market share. Another is that the weekly reports at the SKU level made it impossible for clients to use the traditional modus operandi: inspect the tracking reports, identify changes, find explanations for the changes (subjectively), and determine the desired marketing activities for the next period. Causal explanations were required more frequently, and with the increasing sophistication of (brand) managers, it was natural for econometric models to become popular means for the estimation of marketing effects on sales. Thus, IRI introduced PROMOTIONSCAN (Abraham and Lodish, 1989) and Nielsen developed SCAN*PRO (Wittink et al., 1988). We provide details about the nature of the model-building process which is critical for the successful development of econometric models in Section 3.5.

This discussion suggests that the increased availability of accurate and detailed marketing data has been an important force in the implementation of models. More broadly the data sources include panel and survey data, often collected by computer-aided interviewing and customer transaction databases. These developments result in models that increasingly:

- satisfy Little's implementation criteria;
- are parameterized on a large number of observations;
- account for errors in the data, etc.

[3] See, for example, Bucklin, Gupta (1999) who report findings from an exploratory investigation of the use of UPC scanner data in the consumer packaged goods industry in the U.S.

3.2 Implementable models: some examples of existing applications

Although the applicability of some marketing models to real-world problems has been doubted (Simon, 1994) it is clear that there are many examples of successful applications (Little et al., 1994; Parsons et al., 1994; Lilien and Rangaswamy, 1998, pp. 313-315). Notable developments focus on models of:

- consumers' choice processes (see the special issues of *IJRM* on consideration sets (vol. 12.1) and panel data (vol. 8.3), Seetharaman and Chintagunta, 1998, and the special issues of *Marketing Letters* on choice models[4]);
- consumer behavior heterogeneity (Wedel and Kistemaker, 1989; Wedel and Steenkamp, 1989, 1991; Ailawadi et al., 1999; Wedel and Kamakura, 2000 and the forthcoming special issue of *IJRM* on market segmentation);
- over-time behavior of brand loyalty (Dekimpe et al., 1997);
- product design, innovations and new products (see the special issue of the *Journal of Marketing Research* (February, 1997) and Kim et al., 1999);
- brand equity (Kamakura and Russell, 1993);
- marketing channel operations (see the special issue of *IJRM* on channel productivity);
- sales force decisions (see the special issue of *IJRM* (vol. 7.2/3));
- the optimal selection of addresses for direct mail (Bult and Wansbeek, 1995; Bult and Wittink, 1996; Bult et al., 1997);
- optimal competitive strategies (Gatignon et al., 1997; Kim and Parker, 1999; Shankar, 1999);
- competitive reactions (Plat and Leeflang, 1988; Leeflang and Wittink, 1992, 1996; Brodie et al., 1996);
- short- and long-run demand effects of marketing activities (see also Section 3.5).

The era is also characterized by a latent demand for models by firms. In earlier eras the interface between model builder and model user was probably dominated by the supply side so that analysts offered their models to managers and had to convince the user of potential benefits. Model acceptance by managers is facilitated if model builders can present convincing arguments ex ante why and how models will provide superior marketing decisions. In addition, access to previous applications that demonstrate how other managers obtained benefits should stimulate potential users. Of course, it also matters that a model captures the essence of (repetitive) decisions effectively. Importantly, the statistical analysis of historical data can provide a convenient basis for routine decisions (Bucklin et al., 1998). At the same time the automation of routine decisions allows managers to have more time for creative and other tasks

[4] See *Marketing Letters*, August 1991, October 1994, July 1997, August 1999.

for which models are not suitable. Today managers often ask what type of model, if any, should be used for a given decision.

Examples of marketing decisions that have much potential for model-based automation are:

a. repetitive promotion and pricing programs;
b. media allocation decisions;
c. distribution programs;
d. product assortment and shelf space allocation decisions for individual stores;
e. direct mail solicitations.

3.3 Empirical generalizations

In this mature era scattered empirical results are catalogued and generalizable phenomena are identified, resulting in "laws of marketing". The principal advocate of this approach to model building is Ehrenberg (see, for example, his book on repeat buying (1972) and more recent references (1990, 1994, 1995)). The regularities Ehrenberg has found include the following (Uncles et al., 1995). For most frequently purchased branded goods, the market shares differ strongly across brands, and the shares are positively related to the number of household purchasing the brands. Thus, smaller brands have fewer buyers. In addition, buyers of smaller brands tend to make fewer purchases in a given period. The combination of these two negatives for brands with smaller market shares is often referred to as "double jeopardy".

Other attempts to find generalizable patterns include Leone and Schultz (1980) who observed that the elasticity of (selective) advertising on brand sales is positive but small. In subsequent meta-analyses by Assmus et al. (1984) and Lodish et al. (1995a) somewhat higher advertising elasticities are found. Other meta-analyses focus on the long-term effects of advertising on market response (Leone, 1995; Lodish et al., 1995b) and on intermediate effects such as consumer beliefs and attitudes (Vankratsas and Ambler, 1999).

Apart from advertising, meta-analyses report price elasticities (Tellis, 1988). By contrast, many of the papers in the special issue of *Marketing Science* edited by Bass and Wind (1995) focus on directional relationships. For example, Kaul and Wittink (1995) summarize the nature of price and advertising interaction effects. In the past ten years we have also seen an enormous increase in the number of studies on price and non-price promotions (Blattberg and Neslin, 1990, 1993; Foekens, 1995; van Heerde, 1999). Some of these results have been summarized as generalizations about the effects of promotions (Blattberg et al., 1995). Other generalizations refer to the diffusion of new products, first-mover advantages (VanderWerf and Mahon, 1997), the stationarity of market shares (Dekimpe and Hanssens, 1995a, 1995b), the relation between market share and distribution (Reibstein and Farris, 1995), etc.

3.4 Applications to new contexts

A very large part of the empirical model-based research in marketing pertains to consumer goods. While this is a limitation, it is also true that the persistent modeling of problems in a restricted part of the economy (frequently purchased packaged items) facilitates the discovery of empirical generalizations. Importantly, the successful application of models in one area will stimulate their use in other contexts. Examples are:

- adaptation of a model of the influence of temporary price cuts on demand to a model of coupon effects;
- application of a model, developed for the entire US, separately for each of multiple metropolitan areas, for individual retail chains, and/or adapted to capture heterogeneity between stores (Hoch et al., 1995);
- use of models of scanner data with appropriate modifications in a wide variety of countries;
- modeling of marketing phenomena based on a combination of store-and household-level data (Russell and Kamakura, 1994);
- simultaneous modeling of the decision to purchase from a product category and its timing, to purchase a specific brand, and to purchase a specific quantity (Gupta, 1988);
- simultaneous modeling of the demand for goods and the corresponding marketing activities so that competitive reaction effects are explicitly taken into account (Kadiyali et al., 1999).

The increasing attention to empirical modeling also focuses on questions pertaining to the retailer. Some of the research deals exclusively with the effects of marketing actions on measures of retailer performance while other research considers the interplay between manufacturer and retailer.

The complexity of real-world decisions often makes it difficult to identify the unique role attributable to models when strategic decisions are made. For example, Procter & Gamble's decision in the 1990's to favor an Every Day Low Price (EDLP) strategy over a High Low (HiLo) strategy is partly due to the close cooperation between the firm and Walmart (which has always used EDLP) and the associated learning about benefits that accrue from an efficient supply chain. However, P & G also discovered from promotion models that the temporary gains due to promotions were often illusory and in fact detracted on average from profits especially if the negative consequences on production, distribution and inventory management are taken into account. The partnerships between manufacturer and retailer stimulate further shifts from modeling horizontal competition to the modeling of vertical competition and cooperation, from tactical (e.g. the effects of specific temporary discounts) to strategic (e.g. the benefits of discount policies) decisions, and shifts from optimizing the profitability of a firm to the profitability of an entire supply chain.

The increasing use of models in the consumer goods area (e.g. Bucklin and Gupta, 1999) may also further stimulate the intensity of model building in services and B2B marketing. The latter context in particular requires a different approach, partly due to data characteristics but also due to the large amount of customization. During the first quarter of 2000, several private web-based markets were announced, one for suppliers of the automobile manufacturers, and two separate ones for suppliers to groups of retailers. In this manner, the internet facilitates the communication of opportunities for bids which will have especially noticeable effects on prices paid to suppliers. So far little has been done to capture the critical components of this vastly more efficient decision-making process with models. Yet while the exchange process has moved to the internet, and price comparisons have become more influential on the choice of a supplier, it is natural that over time the focus will broaden to include quality, enhanced services, etc. Thus, there is an opportunity and a need for models to capture the multidimensional complexities that will pervade the internet-based decision-making process in B2B marketing.

3.5 The model-building process

The nature of the model-building process, can be characterized by the stages suggested for model implementation in Leeflang et al. (2000, Chapter 5). We show this process in Figure 1. In this section we describe these steps and we discuss some recent developments pertaining to these parts.

1. *Opportunity identification* is the first step in the model-building process. Here the model builder evaluates whether the use of a model can improve managerial decision making. Attractive opportunities include the exploitation of well-known advantages associated with the use of "models of man" (models of subjective judgments) for repetitive decisions. Models of man offer the advantage of consistency in model outcomes over subjective judgments. However, consistency in predictions does not imply lack of bias. Models of past actual outcomes can overcome the biases that are inherent in subjective judgments. To the extent that the market structure and the relevance of variables are stable over time, or dynamics are properly captured, models of actual outcomes are favored over models of judgments for the prediction of future occurrences.

   All repetitive marketing decisions are candidates for model-based automation. In a world flooded by data and increasing tendencies toward customization, there are many opportunities to use models for decision making in marketing (see Section 3.2).

2. In the *model-purpose* step the intended use of the model is defined. Increasingly, models provide managers with "what if" simulation capabilities so that both short-and long-run effects can be documented, likely competitive reactions can be taken into account, and long run *profit implications* for alternative marketing actions can be considered (Mela et al., 1997, 1998; Dekimpe and Hanssens, 1999; Dekimpe et al., 1999; Silva-Risso et al., 1999). This simulation capability is a natural part of conjoint analysis applications in which preference share predictions are made for a wide range of plausible market scenarios. However, models based on historical data, especially household purchases, offer similar opportunities. Such simulation capabilities in a way approximate the output from *normative* models.

   With regard to models of the effects of promotional activities, Little (1994) advanced their use for the determination of incremental purchases and profitability resulting from (manufacturers) coupons, while Abraham and Lodish (1990) examined the profitability of trade promotions. The evidence appears to indicate quite clearly that most promotions for mature products are unprofitable.

   A shift in emphasis from descriptive to predictive *and* normative models is also reflected in the development of models that distinguish between the sources of sales increases, such as brand switching, store switching, purchase acceleration and category expansion (van Heerde et al., 2000b). Albers (1998) developed a principle that decomposes the profit contribution variance into separate variances associated with the effects of single marketing instruments.

3. The determination of *model scope* is the third step. We expect that models become more complex, more complete and integrated. Survey-based methods will be used "continuously" in a manner that resembles the continuous collection of purchase data. This will facilitate the joint use of diverse data sources and it will allow the customer focus that is so critical in today's environment to become fully developed (see Section 4.2). The business world has embraced the notion that the functional areas of the firm, such as marketing and production, should not act as independent units (Dearden et al., 1999). Increasingly individual activities, nominally belonging to different functional areas, are coordinated and sometimes integrated. The changing role of marketing in the firm (Webster, 1992) or the re-engineering of the marketing function is reflected in models that link marketing decisions to other functional areas. Eliashberg and Lilien (1993, p. 17) expect that "interface modeling" will receive more attention. Examples of models that link marketing to other functional areas are given in Leeflang et al. (2000, Chapter 19).

4. *Data availability*. An important part of the measurement of purchases at the retail level is provided by the following firms (see *Marketing News*, 1999). AC Nielsen

tracks sales, market share, distribution, pricing and promotional activities on a weekly basis in many countries. Scantrack is a reporting device of the activities and results based on weekly scanner data in food, drug, mass-merchandise and other outlets. AC Nielsen also employs a panel of 52,000 US households who, equipped with in-home scanners, record their purchases in a wider variety of outlets. An additional 74,000 non-US households provide similar data. IRI offers InfoScan, a tracking service that provides weekly sales, price and store-condition data in food, drug and mass-merchandise outlets. This service also has information from a panel of 60,000 households whose supermarket purchases are recorded by checkout scanners. An additional panel of 55,000 households reports purchases based on in-home scanners. IRI also offers Behaviorscan which measures the effectiveness of TV advertising and tests new products based on field experiments in up to six small markets.

In Europe consumer tracking and other services are provided by IRI/GfK, AC Nielsen and by other firms. GfK offers consumer purchase information in 20 European countries. It has a Europanel of 70,000 households in 26 (European) countries. GfK also monitors sales for consumer durables and services in 36 countries worldwide.

All of these firms provide a variety of modeling services based on household and/or store-level data. Thus, even if clients obtain weekly tracking reports that show the performance and marketing activities for individual items *aggregated across stores,* they can also obtain, from GfK, IRI or AC Nielsen, standardised or customised analyses of store- (or household-) data. However, many clients do their own analyses or use other service providers for model building on market-level data. Since stores tend to differ in marketing activities, the use of aggregated market-level data not only covers up store differences (Hoch et al., 1995) but can also distort the estimation of average marketing effects if a nonlinear model is applied to linearly aggregated data (Christen et al., 1997).

The weekly store-level data show performances and activities aggregated across the households visiting a store. Here the aggregation is not harmful for model building, because households visiting a given store are exposed to the same marketing activities within a given week. However, the typical store-level model does not accommodate heterogeneity in household preferences and in sensitivities to marketing instruments. Some current research includes attempts to not only accommodate but also to recover household heterogeneity from store-level data (e.g. Bodapati and Gupta, 1999). To the extent that household data are “representative” (see e.g. Leeflang and Olivier, 1985; Gupta et al., 1996) and plentiful, these disaggregate data provide the best opportunities for managers to obtain a complete understanding of marketplace complexities in stores equipped with scanners.

We emphasize that both household- and store-level data can provide meaningful insights about marketing phenomena. An important advantage associated with household data is that household heterogeneity can be fully exploited. On the other hand, for relatively infrequently purchased goods, household data are often insufficient due to sparseness. In addition, while the representativeness of household data appears to be acceptable (Gupta et al., 1996), for small cities in which a cooperating household uses the same plastic card in all outlets, there is uncertainty about the representativeness in metropolitan areas. Both AC Nielsen and IRI issue personal wands to probability samples of households, and these households are expected to (re)scan all purchases in relevant categories at home, for all frequented outlets. Although scanning is a lot easier to do than maintaining a diary, it is still a much more onerous activity than having a plastic card swiped. And in Europe many purchases occur in small shops which are often not equipped with scanners, leaving potentially large gaps in coverage (van Heerde, 1999, p. 20; Bucklin and Gupta, 1999). These conflicting considerations suggest that managers will benefit most from models that *combine* household and store data. A promising example of joint usage of multiple data sources is Russell and Kamakura (1994).

At the same time new data sources emerge from internet surfing (and purchases) and experimental time-series data such as, for example, eye-tracking data (Pieters and Warlop, 1999; Pieters et al., 1999).

5. Little (1970) argued that models should satisfy certain criteria to increase their chance of being implemented. These *model-building criteria*, related to model structure, ease of use and implementation strategy will be generally accepted as the use of models becomes commonplace in many areas of marketing decision making.

6. The availability of scanner data has had a tremendous effect on the opportunities for model *specification*. In the first three eras of model building in marketing, the emphasis is on models for a single brand specified at the brand level. Now we see models specified at the SKU level, covering multiple own- and other-brand items, where competition is defined at the product category level and sometimes covers multiple product categories (Chen et al., 1999).

   Due to vast improvements in the disaggregate nature of data and the continued development of theoretical and analytical models, we expect increased applications of:

   - empirical game-theoretic models with an emphasis on horizontal competition (Vilcassim et al., 1999);

- theoretical game-theoretic models of cooperation and vertical competition in the distribution channel,[5] including web-based alternatives;
- time-series models with explanatory variables (Dekimpe and Hanssens, 1995a, 1995b; Franses, 1996, 1998);
- mixture- and other models for market segmentation (Wedel and Kamakura, 2000).

7. *Parameterization*. Increasingly sophisticated models and estimation methods allow managers to accommodate the details of individual activities. Researchers use *nonparametric* and *semi-parametric* estimation methods to allow the functional form of main- and selected interaction effects to be determined by the data. The results often show dramatically different effects than those implied by parametric estimation of models with transformed variables (Abe, 1995; van Heerde et al., 1999).

   Other developments include an increasing use of methods such as:
   - Generalized Method of Moments (GMM) (Chintagunta, 1992);
   - Structural Equation Models (SEM), including Instrumental Variables (IV) (Gasmi et al., 1992; Kadiyali, 1996);
   - Hierarchical Bayes methods (Lenk et al., 1996).

8. The use of "diagnostic predictive validity" will have its impact on the *validation* step. This recently developed approach diagnoses the role of data characteristics in *validation* samples on forecast accuracy. The benefits of diagnostic predictive validity are that:
   - one can determine under what conditions one model tends to outperform another model;
   - one can decompose the bias component into specific sources;
   - the data characteristics are taken into account (i.e. the validation result depends on and varies with data characteristics).

   For some examples of applications, see Foekens et al. (1994) and Leeflang et al. (2000, Chapter 18). We argue that this approach is superior in assessing a model for the accuracy of conditional predictions relative to the frequently used method of cross-validation.

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5 Examples are studies on guaranteed profit power (Krishnan and Soni, 1997), manufacturers' returns policies (Padmanabhan and Png, 1997), and manufacturers' allowances and retailer-pass-through rates (Kim and Staelin, 1999). Many of these studies, however, lack empirical validation.

9, 10, 11. The last three steps of the implementable model-building process are (9) *cost-benefit considerations*, (10) *use* and (11) *updating*. If standardized models are implemented because the essence of repetitive decisions can be captured effectively, or a given model structure has wide applicability, the *benefits* of models increase. Standardized models may offer especially attractive opportunities for evolutionary model building. If many managers use a specific model, they gain experience with the model's usefulness for decisions, and shared experiences will facilitate the identification of shortcomings. The model structure can then be expanded to account for additional complexities and dependencies. Leeflang et al. (2000, pp. 536-537) discuss an evolutionary process with respect to the SCAN*PRO model. Expanded versions of that model, such as a model with leads and lags in promotional effects (van Heerde et al., 2000a), a model that accommodates flexible main- and interaction effects estimated by semi-parametric methods (van Heerde et al., 1999), a varying parameter model (Foekens et al., 1999), and a "master model" (van Heerde et al., 2000b), which can be used to decompose incremental sales separately for each deal magnitude and promotion signal (display, feature), have resulted from such an evolutionary process. Naturally, the cost of models decreases with standardization and enhanced usage.

There are ample opportunities to increase the *use* of models for marketing decisions. Any resistance on the part of managers can be overcome if managers actively play against the model so that conditional forecast accuracies can be compared. Importantly such comparisons also allow the user to identify reasons for differences, and this can lead to insights about the possible benefits of combining models and judgments (Blattberg and Hoch, 1990).

Once a model is accepted, it is important for users to check the accuracy of conditional predictions on an ongoing basis. These accuracies can be compared with what would be expected based on (initial) model estimation and testing. In addition, the forecast accuracies can be tracked over time against various conditions. This tracking provides the model builder with an opportunity to identify the weakest aspects in the model and to respecify and/or *update* the model's parameters.

Decision-automation in marketing is facilitated by the development of advanced marketing management support systems. Wierenga and his associates (Wierenga, van Bruggen, 1997; Wierenga, Oude Ophuis, 1997; Wierenga et al., 1999 and Wierenga, van Bruggen, 2000) discuss the virtual explosion of these systems ranging from "information systems" to "marketing creativity-enhancement programs". Lilien and Rangaswamy (1998, Chapter 11) expect that during the next decade major developments in technologies to support marketing decisions will be geared to help managers process the information that is already available to them. "Marketing engineering" (i.e. the use of decision models for marketing decisions) will evolve along three dimensions. Specifically, Lilien and Rangaswamy expect: (1) more diversity in types of users (not only analysts but also managers will use models); (2) models used not only for forecasting and optimization/allocation but also for explanation and simulation; and (3) a shift from information systems to "intelligent" systems such as expert systems and systems for group decisions.

4. The Future

4.1 New Marketing

In the previous section we discussed a model-building process that is suitable for traditional marketing. Briefly, marketing is assumed to be about the use of the 4 P's to affect demand. Modeling of "causal" effects on aggregate measures of demand will grow, we believe, because managers will recognize the positive benefits of demand function results on the profitability of marketing investments. Models can provide unbiased estimates of the marginal effects of changes in individual variables, whereas subjective judgments are subject to numerous biases such as prominence effects, anchoring effects, and overconfidence. Interestingly, Van Bruggen et al. (1998) find that managers who use a Decision Support System (DSS) are less inclined to anchor their decisions on earlier decisions compared with managers who do not use the system. Similarly, we imagine that prominence effects, and overconfidence and other biases will be reduced for managers who use model-based results relative to managers who do not. The incorporation of model-based results into a DSS should then be especially beneficial. Thus, there are important issues in need of further research to guide the actual use of models for marketing decisions.

At the same time, the market environment is changing rapidly in ways that may make current assumptions untenable. For example, traditional models treat regular and/or promoted prices as exogenous variables (although this assumption has been relaxed in recent papers such as Kadiyali, 1996; Besanko et al. 1998; Villas-Boas and Winer, 1999). Increasingly, however, in both B2B and Business-to-Consumer (B2C) markets, the customer has the opportunity to bid on prices. To the extent that the effective price paid varies between customers based on, say, the customer's price sensitivity, it is impossible to justify treating price as an exogenous variable.

The validity of traditional model-based results is further reduced by the increasing use of those results by managers to differentiate the marketing programs between regions or chains and ultimately between customers. Subsequent modeling efforts will then have to capture the effects of truly random deviations from the predetermined levels of marketing efforts. Modelers should talk with the decision makers

responsible for past marketing efforts so they understand the reasons for variation in marketing activities and have model-building efforts that reflect this understanding.
The internet and related technological developments facilitate the analysis of purchases at the customer level. This presents further opportunity to improve our understanding of (heterogeneity in) the response to marketing activities. The huge volume of data now commonly produced is, of course, both a blessing and a curse. An important advantage is that we can learn much more about individual differences and tailor marketing programs accordingly. Yet the data files become extremely large so that commonly used criteria need to be adapted (Granger, 1998) or the databases have to be reduced so that, for example, only information on the best customers remains. In either case, the availability of large databases creates a demand for new models and methods (Balasubramanian et al., 1998).

We propose that models in the future cover both strategic and tactical issues. For example, competing retailers need to know how consumers choose between them as a function of assortment, qualities, prices, order placement, delivery, etc. Broadly speaking we imagine that sellers differentiate themselves based on variations of the three value disciplines suggested by Treacy and Wiersema (1993), viz. operational efficiency, customer intimacy and product leadership. Walmart excels in "operational efficiency" and Webvan (an internet-based grocery operator) and others can excel in "customer intimacy" (see below), so that the traditional supermarkets may want to concentrate on other benefits not easily provided by these operators. One interpretation is that some retailers may be repositioned to provide the latest new products (consistent with "product leadership") and existing products in a manner that makes the shopping experience exciting. Some supermarkets in the U.S.A. already provide an unusually attractive combination of fruits and vegetables, high-quality meat and fish, delectable coffees and desserts, etc. Consumers can have selected items prepared for consumption in the store by chefs at no extra charge. Throughout the store, consumers can also try new products or existing products prepared in new ways.

Although it is possible to track individual purchases under each of these value disciplines, the customer intimacy model makes this especially easy. Webvan can learn from the web-based order process how individual households make decisions and it can focus on repeat purchase patterns. It can also easily determine the contribution to profits from each consumer, and reward loyal consumers accordingly. Since consumers will not learn about new products through in-store samples, Webvan can add free samples either to all orders or selectively to individual consumers based on a combination of profit contribution and fit with past purchase patterns or expressed preferences (à la Amazon.com).

Consistent with this idea is the general shift in marketing from a focus on brands (and an organizational structure based on brand- or category managers) to customers (and a structure based on customer managers). In this manner, the internet facilitates the customization of marketing across households similar to what has been used in industrial marketing by sales- and service managers for a long time.

4.2. New modeling approaches

Future modeling approaches will reflect a new marketing paradigm: a firm selects those customers for or with whom it can offer products and services better than other firms can, and with whom it can develop long-term relations such that each customer directly or indirectly contributes positively to the firm's expected profits (Hoekstra et al., 1999 call this the "customer concept").

We show in Figure 2 a simple framework that reflects the role the customer plays. We use this proposition as a basis for the identification of models that are especially suitable in the future. In this framework we distinguish six steps:

a. We propose that a firm first identifies preferences of potential customers for such benefits as quality, reliability, convenience, services and price. We envision the modeling in this stage to be broad such that firms can identify the market potential for alternative value disciplines. Variations of conjoint analysis may be suitable to capture tradeoffs at the individual level. This modeling process needs to be updated regularly since preferences may change rapidly (Wittink and Keil, 2000).

b. Heterogeneous logit and probit models of individual choice behavior will be useful to capture the marketing mix effects. Under certain conditions it will be efficient to combine actual choice data with hypothetical choices gathered in conjoint choice experiments. The models can combine category purchase (timing) decisions, brand choices and quantity decisions (Gupta, 1988). If the customer data are insufficient, unavailable or unrepresentative (see Leeflang and Olivier, 1985; Gupta et al., 1996), models that account for and potentially recover household heterogeneity from store-level data (Bodapati and Gupta, 1999) may be used.

c. In a third step firms determine customer satisfaction. This concept is usually operationalized based on a comparison between benefits delivered by the firm (perceived by the customer) and customer expectations. In this manner customer satisfaction models can show the roles uncontrollable and controllable factors play in the formation of expectations and the influence of the same on perceived benefits with respect to the purchase as well as the consumption experience.

d. Models of customer satisfaction can show the critical drivers of satisfaction. A limitation of these models, however, is that satisfaction cannot be the ultimate goal. For managerial purposes, changes in the benefits delivered need to be linked not only to expected changes in satisfaction but also to expected changes in repeat purchases and word-of-mouth. With those linkages it is possible to simulate alternative investments in marketing and choose those with the highest expected pay-off. Survey data on satisfaction and repeat purchase intent can be related to purchase data showing retention. New marketing models will focus on customer profitability as a function of retention, and retention as a function of reward programs, etc.

e. Through the explicit linkage of changes in the benefits delivered and changes in repeat purchase it is possible to determine the expected contribution of investments in products, services and other marketing support to expected profits. In mass customization these questions can be considered at the individual level so that differentiation is possible between customers according to future profit potential. Thus, the various models together, whether applied sequentially or simultaneously, form the basis for the determination of each customer's contribution to profits. The traditional economic criterion used to evaluate marketing investments in brands now becomes applicable to customers: they are treated individually such that the criterion "marginal revenue equals marginal cost" applies to investments in each individual customer.

f. Finally, if we use a broader perspective we consider marketing investments in terms of their effect on the firm's market capitalization. It is well known that accounting profits do not translate directly into investors' market-based valuation. For example, capital markets may favor long-term revenue growth over short-term profit. Explicit treatment of market capitalization as the ultimate goal may therefore lead to different marketing investment strategies than an orientation toward accounting profits would suggest.

We use the grocery industry to provide a brief illustration of how models can be applied to the six stages in Figure 2. Technological developments allow for vastly enhanced services including home delivery. Peapod was among the first to allow internet-based ordering and to provide home delivery through alignments with existing supermarkets (Pine II et al., 1995). As the competition for home delivery of grocery purchases intensified, Peapod's model of having employees do the shopping for customers in traditional supermarkets became obsolete in the face of more efficient alternatives. Webvan and other firms takes a more radical approach by eliminating the store alltogether.

If it is reasonable to propose that consumers' preferences can be categorized according to the three value disciplines offered by Treacy and Wiersema (1993), then the first stage in Figure 2 requires models that quantify the benefits provided by each of these options for the determination of the specific features of individual retailers.

For example, conjoint analysis can be used to determine whether Webvan should or should not have inventories in its warehouse based on a trade-off between price and delays in delivery. The results of this modeling approach can be updated over time to determine how Webvan's characteristics should be adapted from the perspective of both current and potential customers.

In a second stage revenues as well as individual purchases can be modeled as a function of marketing variables with recognition of endogeneity of the marketing variables. Opportunities exist for Webvan to make specific suggestions to individual customers (either on the internet or by adding free samples to the baskets or both) based on principles originally developed at Amazon.com for books. The internet not only facilitates two-way communication but it is especially suitable to aid consumers with the selection of items based on customized criteria. Every consumer may want to consider quality and price but the dimensions of quality will vary across consumers as will the manner in which these two aspects are combined.

The third stage relates the order process characteristics, the variety and quality of items from which consumers can choose, the delivery experience, etc. to customer satisfaction. We advocate that the firm adopt satisfaction of customers (but also of employees and suppliers) as a central objective. This argument is based on the premise that the pursuit of customer satisfaction leads to (increased) sales and profits. By linking intent to repeat purchase and favorable word-of-mouth to customer satisfaction and to marketing investments, it is possible to identify the investment opportunities with the highest expected contribution to profits. We note that it will be especially instructive for managers to have models of word-of-mouth and social influence processes. The internet facilitates interaction between customer targets, and technological developments allow managers to model the dependencies of purchase behavior or preferences on those processes.

Although models of customer satisfaction and repeat purchase intent are typically estimated from cross-sectional data, the desired customization of products, services and marketing support makes it critical for those models to accommodate heterogeneity so that customer profitability can be expressed at the individual level. It will be especially meaningful to explore how reward programs and other events influence both current purchases, retention and revenue growth.

Finally, if we use the ultimate objective of shareholder value maximization, investments in marketing and in other areas need to be evaluated from the perspective of the expected contribution to market capitalization. It will be helpful to quantify the preferences of selected shareholders and influential analysts with respect to alternative combinations of revenue growth, profit and other measures so that managers can choose among alternative investments in a manner that is consistent with this ultimate objective. Investments in marketing activities can then be evaluated with respect to their expected effects on market capitalization.

Importantly, web-based developments facilitate the collection of much more detailed databases, the integration of purchase data with continuously collected survey responses and the use of more complex estimation methods to accommodate heterogeneity in preferences and sensitivities but also the endogeneity of prices, promotions and advertisements. Thus, models for marketing decisions will reflect developments due to electronic home shopping, electronic communication (word-of-mouth may become a formal, quantified variable), private bargaining and negotiation, continuous customer-based and firm-directed individualized new-product and service development, just-in-time customized advertising and promotion, etc. from the perspective of market capitalization.

These proposed modeling approaches partly resemble existing efforts. For example, there is a rich literature on models of trial purchases, models of repeat purchases, models of satisfaction, etc. We propose that these various components be linked, and that all relevant marketing activities be linked to various individual behavioral, attitudinal and intention measures. The linkages are critical so that market simulations can be conducted. These simulations should allow the user to compare alternative marketing programs in terms of short- and long-term impact on revenues, profits and market capitalization. The adage that it is a lot cheaper to retain an existing customer than to attract a new one will show up in investment considerations. That is, the return on investment in keeping existing customers should then be vastly higher than the return on the same amount invested in finding new ones.

These ideas depart, however, strongly from the traditional market response modeling approaches. Market share matters but only as an end result not as an objective nor as a criterion variable. This is because it can only be defined when the market definition is known and relatively stable. In today's world the marketplace is rarely sufficiently stable. Folgers' share of packaged coffee sold in supermarkets was a misleading measure of performance when Starbucks introduced special coffee outlets. In addition, the use of market share implies that all sellers included in the market definition compete more or less equally.

In today's environment, customer share should replace market share, customer managers should replace brand managers, and customer profitability should replace product profitability. Many B2B firms have long been guided by customer-focused principles, in part because they often have a limited number of customers. With the vast increases in information technology it is now possible to apply these ideas in consumer markets. Financial service and transportation firms appear to be making steady progress in this direction. Large retailers are following quickly. Through the use of bonus cards, some supermarkets now know that roughly 30 percent of the (card carrying) customers account for 70 percent of total revenues, and 20 percent account for 80 percent of total profit. These same firms work with research suppliers so that they can differentiate, for example, between customers who are loyal to one supermarket but spend modestly and customers who spend a lot across multiple supermarkets but spend modestly at the focal supermarket. Importantly the focus on customer share and other customer-based measures will force the research suppliers to gather complete data on all expenditures in a given category. Measures based on scanners would be supplemented by, say, survey-based measures of relevant purchases at outlets not equipped with scanners. If such services had existed at the time Starbucks entered the coffee market, Procter & Gamble's managers of Folgers coffee would have recognized the opportunity for high-quality coffees and related services much faster than they did.

The proposed change in focus, from aggregate measures to measures of individual customers, to the integration of hard (trial, repeat, loyalty) and soft (preference, satisfaction) data, and to linking the various elements so that simulations of the effects of marketing investments in individual customers on profits can be completed, will have the following effects. Marketing decisions will be considered explicitly in terms of the identification of target market characteristics which will increase the match between what consumers want and what suppliers provide. This is accomplished by mass customization of the products and services offered, and by adjusting the offerings over time. Models of purchases will identify the effects of marketing variables in various forms on attracting customers. Other models will show the effects of a partly overlapping set of variables on customer retention. Relatively new forms of variables will be included in the latter equation, for example, loyalty programs, unexpected rewards and special services.

Sellers will also explore the opportunity to offer long-term contracts to individual customers based on models that capture the benefits of lock-in. Strong relations with the best customers and two-way communication will create higher levels of loyalty. The result is that profit will increase because the closer match between supply and demand reduces price sensitivity, increases customer satisfaction and loyalty, and this enhances the customer lifetime value to the firm. Importantly, this result is obtained based on integrated models of individual customers.

4.3. Another perspective

The internet-based market environment facilitates customization of products, services, prices and supporting programs. However, if customers specify the product and service characteristics, indicate which prices they offer for those products, and request information at the time they are contemplating a purchase, many of the variables that have traditionally been treated exogenously become strategic decision variables. One possible implication is that sellers will use the observable choice behavior primarily for tracking purchases and that experimental manipulations will become standard operating procedures for the estimation of the effects of alternative communications, reward programs, prices, etc. on trial, intent to repurchase, word-of-mouth intent and other measures.

Although we can imagine that the future allows manufacturers to deal directly with consumers (disintermediation), and in this manner become more informed about consumer preferences and sensitivities than ever before, it is also plausible that new agents will provide essential services. In a world of brick-and-mortar retailers it is impossible for consumers to optimize their purchase behavior. This is partly due to the excess of information that is available in the marketplace. But it is also due to the fact that manufacturers and retailers are partial and cannot be objective in their interaction with consumers. Electronic commerce will bypass at least some intermediaries so that consumers should be able to make their choices with less interference by sales people. Yet, although it is relatively convenient for buyers to identify the lowest possible price available from all internet-based suppliers, it is impossible for consumers to truly maximize utility functions. Their utility depends on such dimensions as taste, nutrition, pleasure, energy and health, which derive from the purchase and consumption of all items selected from the hundreds of thousands available.

A plausible scenario is that consumers will make use of infobots (information robots) that do not just provide comparative data on alternatives but also quantify each individual consumer's utility (preference) function. If this function has a sufficient amount of detail, and the infobot has access to the correct information on all relevant dimensions for all available products, it will be possible for the infobot to create one of more baskets of goods that provide the highest possible marginal utility for the individual consumer. The infobot can give personal advice to a consumer about consumption options with each option scoring high on her utility function so that she can select one more or less arbitrarily.

As infobots become more fully developed, they can include extensions that allow for dependence on past consumption, for joint utility maximization (with partners, colleagues, etc.) based on mixtures of on-premise and at-home consumption, for timing of consumption relative to work, leisure and sport activities, etc. In this manner the maximization of utility is not only customized but is also dynamic and incorporates various complexities that have received some attention in the marketing literature (e.g. Krishnamurthi, 1988, who studied the formation of joint preference functions, and Walsh, 1995, who considered purchase decisions in the face of uncertain future preferences). Ultimately, an infobot should allow the consumption of all items within a given period of time to be jointly maximized. The set of items may include prescription medicine, vitamins, herbs and other relevant interventions together with food, entertainment, education and other goods and services, so that interaction effects between the items on overall utility can be taken into account.

We note that for this world to materialize, all suppliers must provide the relevant information on the web, and update it continuously. Independent agencies should determine the accuracy of all information provided. Suppliers can infer estimated utility functions from each consumer's purchases and survey responses, as discussed in Section 4.2, and adjust products, services and marketing programs accordingly.

Consumers will also update their utility functions over time, and the suppliers will attempt to predict the nature and the timing of such changes. In this manner consumers can become vastly more efficient and effective in maximizing their utility functions. Their infobots can also help consumers overcome many biases and shortcomings such as hindsight bias, overconfidence and anchoring effect. In this sense an infobot can serve as a Consumer Decision Support System (CDSS). Under this scenario, suppliers will be more heavily dependent on intelligent decision support systems, continuous tracking and sophisticated models, to keep up with the increased sophistication and rationality of consumer decisions.

5. Conclusions

Model building for marketing decisions has become an important part of management practice in many firms (Bucklin and Gupta, 1999). The quality of model-based support has increased enormously due to the availability of large-scale databases and application of the latest estimation methods. In the twenty-first century we expect that marketing managers will increasingly customize products and services and the supporting marketing programs. To support this, model builders have to identify the structure and specification of models that meets this objective best. In this regard we expect convergence between academicians and practitioners. The academic world is increasingly interested in the production of relevant research, partly due to growth in executive education and perhaps also due to reduced access to governmental support for research. Practitioners are willing to provide promising data because they recognize the benefit of sophisticated analyses academicians are capable of. Thus, there is a natural basis for cooperation and the interaction will stimulate the further development of implementable models.

We propose that the new marketing will consist of customer preferences measured on an ongoing basis, as is common for consumer choices of products and is becoming customary for customer satisfaction. To the extent possible these three sources of data will be integrated and analyzed jointly. We note that preferences, choices and satisfaction levels are largely complementary in the sense that preferences are typically modeled as a function of product characteristics, choices as a function of marketing activities, and satisfaction levels as a function of both.

All modeling efforts should allow for aggregation across customers at the last possible moment. For example, predicted choices and retention rates should be aggregated so that managers can predict changes in revenues, profits, etc. under a variety of simulated scenarios. These simulations allow managers to predict the effects of new products/services, repositioning, price changes, promotions, advertising, distribution and reward programs on customer retention and other measures discussed earlier. By contemplating the likely reactions of other suppliers and predicting consumer response to those reactions, managers can also take market dynamics into account. In this manner, they can use the models to predict equilibrium results after a series of multistage decisions.

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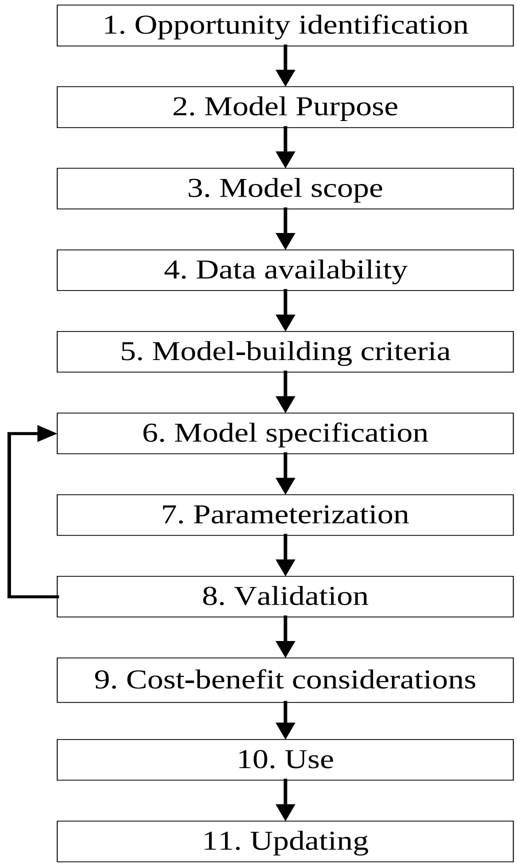

Figure 1 Stages in the model-building process with a focus on implementation.

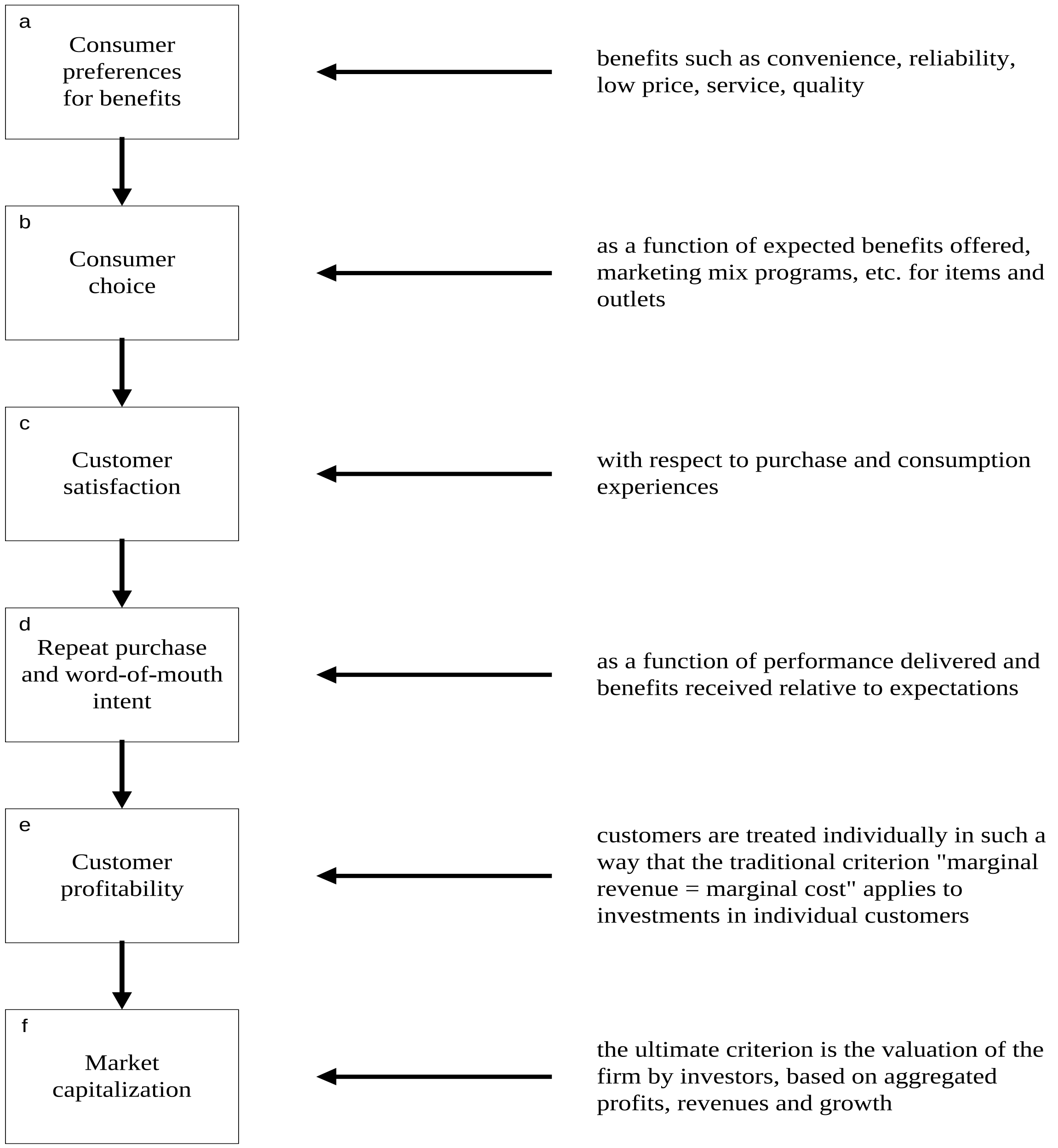

Figure 2 From consumer preferences to market capitalization.