Marketing Letters 9:3 (1998): 235–246

From Decision Support to Decision Automation: A 2020 Vision

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Abstract

The authors discuss the long-run future of decision support systems in marketing. They argue that a growing proportion of marketing decisions can not only be supported but may also be automated. From a standpoint of both efficiency (e.g., management productivity) and effectiveness (e.g., resource allocation decisions), such automation is highly desirable. The authors describe how model-based automated decision-making is likely to penetrate various marketing decision-making environments and how such models can incorporate competitive dynamics. For example, the authors foresee that close to full automation can ultimately take place for many decisions about existing products in stable markets. Partial automation could characterize decision making for new products in stable markets and existing products in unstable markets.

Key words: Decision support, automation, competition

Introduction

In the last two decades, the concept of bringing together data, models, and computing power to help the marketing manager has grown from optimistic beginnings (e.g., Little 1979) to full scale revolution in the use of information in marketing decision making (e.g., Blattberg, Glazer, and Little 1994). Indeed, much of the research in marketing science has been oriented to the development of tools and methods that *help* managers understand their markets and make decisions (e.g., Neslin et al 1994). If this has been the age of marketing decision *support*, we foresee that the next two decades will usher in the era of marketing decision *automation*. In other words, the decisions we can support today are prime candidates to be decisions we can automate tomorrow.

In this paper, we argue that an increasing proportion of marketing decision-making can be automated. Several forces will drive long-term growth in decision automation. First, the ability to use models to make decisions will provide firms with opportunities to achieve significant gains in the productivity of the marketing function. Second, model-made decisions are likely to outperform manager-made decisions for a growing number of products and markets due to improved quality and availability of data and the inherent limitations of managers in information acquisition and processing. Lastly, automated decision-making is developing a growing track record of success, notably in electronically mediated commerce where very large numbers of decisions must be made in realtime.

While automation is likely to grow, it is not our view that all marketing decisions should be automated. We expect to see more automation for decisions regarding existing products and less automation for decisions pertaining to new and innovative products. We also expect more automation of decision-making in markets that are stable than in markets that are turbulent.

A significant challenge to the successful automation of marketing decision-making will be the engineering of model-based systems to suitably account for the actions and reactions of competitors. The manner in which these competitive dynamics are handled will also need to vary with the nature of the decision-making environment. In stable markets where decisions involve the maintenance of existing products, competitive dynamics may be incorporated via empirical reaction functions and sensitivity analyses. In many instances, they might even be safely omitted from the modeling system. More complex decision-making environments will see the incorporation of new forms of game theoretic analysis, capabilities analysis, and scenarios based on analogous markets.

We are *not* forecasting the demise of the marketing manager. What we are predicting is that marketing decisions *made by managers* may shift from the short-run, the tactical, and the maintenance of the established to the long-run, the strategic, and the launch of the innovative. Indeed, our outlook is quite positive. Tomorrow's marketing manager will enjoy more leverage, spend more time on "the hard important problems," including the rules for automation, and focus on decision domains where data are scarce and models do not yet work well.

Forces driving decision automation

We foresee three factors that will drive the transformation from marketing decision support systems to marketing decision *automation* systems: (1) enhanced productivity in the marketing function, (2) better decision-making and therefore higher returns to marketing investments, and (3) the demands for mass customization of marketing activities.

Enhanced productivity

The marketing manager is often involved in making large numbers of relatively simple, repetitive decisions (both over time as well as across geographic areas and SKU's). This is typified by the product market environments that characterize the marketing of consumer packaged goods. For example, Armstrong (1996) notes that managers at Ocean

Spray Cranberries, Inc. (a medium-sized consumer products company) make decisions across the marketing mix (e.g., pricing, trade promotion, coupons, media advertising, etc.) for 15,914 different items sold in 429 geographies.

Not only are marketing managers faced with the task of making large numbers of repetitive decisions, but the information available to aid this decision making is wide reaching and growing in complexity. According to Armstrong (1996), managers at Ocean Spray have access to 179 measures for 352 historical time periods. In distribution, for example, historical tracking of All Commodity Volume (ACV) by item has been augmented by points of distribution, average number of items stocked by store, and average number of items stocked in stores selling a given SKU. Pressure to consider more and more variables (e.g., four distribution facts instead of one) carries the risk of making each decision more labor intensive. If left unaddressed, this potential hidden cost of the marketing information revolution could actually *reduce* the decision-making productivity of the marketing manager.

In sum, automation can offer firms efficiency gains by freeing the manager from the burdens of routine information processing and decision making. These efficiency gains are likely to become more salient and more sought after as the amount of information bearing on each decision increases. Indeed, firms may be forced to turn to automation to avoid declines in labor productivity within the marketing function.

Improved decision making

An even larger and more significant potential benefit of decision automation is the possibility that model-based decisions may improve upon those made by managers. This is most likely to occur when models and managers have access to *identical information sets*. When this is the case, models have advantages in terms of (i) the amount of information they can process, (ii) the ability to identify patterns in data, and (iii) consistency in prediction. We expand on these advantages below.

The picture is not as clear when models and managers operate on different information sets. When managers have expert judgment (i.e., insights about functional relationships or data) that has not been incorporated into an automated process, the best use for model-based systems for decision-making is probably in a hybrid fashion. For example, Blattberg and Hoch (1990) demonstrated—for certain settings—that a hybrid system of 50 percent manager, 50 percent model will outperform either manager or model alone. The mix does better because it overcomes the weaknesses of both. The model corrects for the human's shortcomings in information acquisition and processing while the human picks up on cues, patterns, and information not yet incorporated in the model. Of course, if the manager's special expertise or knowledge can be codified, it should become part of the model and lead us back to the case of the identical information set.

When this information set is the same, we argue that managers are at growing disadvantage to models. Part of this is due to human limitations in information acquisition (Simon 1957). Even world-class experts may be unable to compete against models as the amount of codable information expands exponentially (consider the parable of Deep Blue versus Kasparov in chess). Because the amount of relevant data that a model can handle far exceeds the data that can be utilized by a manager, the gap will widen as model-based systems begin to draw upon larger and larger information sets.

Consider, for example, the plans of Information Resources, Inc., and ACNielsen to offer their consumer packaged goods clients census data on supermarket sales encompassing some 30,000 stores in the U.S. Because a model can handle *all of the data* at any level of aggregation desired, the natural cognitive limitations of the manager in information acquisition become more salient. A natural response to this type of "information overload" is to conduct analysis at higher levels of aggregation (e.g., the entire U.S. versus regional markets, markets versus accounts, accounts versus stores). Unfortunately, aggregation often leads to potentially severe biases (Christen et al 1997). Alternatively, managers may ignore potentially relevant data and hone in on a few facts about their key accounts, over-emphasizing certain aspects (e.g., competition versus customers, Boulding et al 1994). One advantage of decision support systems is that they systematically expose managers to information that may be ignored due to availability or controllability biases.

Unfortunately, mere exposure does not guarantee accurate use (Glazer, Steckel and Winer 1992). Armstrong (1996), for example, reports managers basing their decisions on mostly descriptive and "amateur" analyses despite easy access to an extensive and well-organized bank of scanner data. Thus, another important reason why models can outperform managers is their biases in information use (i.e., information processing). Substantial evidence exists that managers are not very good at interpreting probabilities and other information and are overly influenced by context and framing (Russo and Shoemaker 1989, Bazerman 1994). Given how difficult it is to train people to overcome these biases, an intermediate solution is to present the information in order to compensate for the bias (e.g., highlight information that tends to be underweighted).

Managers often rely on case-based reasoning and such "pattern recognition" processing is generally regarded as the predominant problem solving style of marketing managers (e.g., Hoch and Schkade 1996). One difficulty with pattern recognition is that the problem solving task grows increasingly burdensome as the number of observations and variables available for analysis and pertinent to the decision increases. While pattern recognition breaks down as a problem solving tool under this burden, it also suffers in the decision-making setting where managers have too few case observations and are prone to over generalize. For these reasons, we expect that good managers will turn increasingly to model-based problem solving. From there, the next step is automation.

Even when managers acquire the relevant information and process it well, there is still room for error. Indeed, a *model of the manager* will generally do better at predicting new cases because it is not encumbered by variation in application (e.g., the results on bootstrapping in Dawes and Corrigan 1974). Managers also often project their own utility functions and behaviors on others (Moore and Urbany 1994). Assuming others share your goals and values can be as disastrous in business decisions as it is in international relations. Finally, managers also have a tendency to "over-steer," reacting to random events and false wind-shifts.

In summary, managers often gather partial information, sometimes interpret it inaccurately, ignore differences in goals, and lack patience. Thus, it is not surprising that decision support systems can improve decision-making and, in many cases, models can outperform managers in repetitive tasks. Just as there are production and process activities better and more efficiently done by machine than by labor, there are decisions in marketing that may be made better and more efficiently when they are automated.

Micromarketing and mass customization

A third force driving automation is the growing ability (and demand) for firms to customize their marketing activities to smaller and smaller units—individual stores, customers and transactions. For example, data exist today to tailor assortments and shelf space in individual stores to the purchase patterns of the customers in local trading areas. At an even finer level, marketing to "segments of size one" requires not only customized product offerings (e.g., Dell Computers built to order), but customized information and individualized pricing and promotion. Correspondingly, however, the number of decisions is enormous and can only be handled on any useful scale by automation.

Numerous examples of partial automation in the pursuit of individualized marketing are already in place, including the targeting of direct mail solicitations, loyalty reward and frequent shopper club programs, and coupon targeting (e.g., Catalina's check-out system). The World Wide Web provides a vivid example of how marketing customization is being married to automation on an even more comprehensive scale. Web-based transactions can provide customized products, pricing, and marketing communications via realtime presentation of materials tailored to the historical and current responses or requests of the customer.

The task of developing models and systems for Web marketing is nontrivial. Agents roam the Web, building and posting tables of price comparisons at independent sites supported by advertising. Web retailers need agents to monitor these sites and game theoretic models to determine appropriate rules of pricing behavior. Furthermore, retailers need to devise programs to enhance customer loyalty through non-price benefits. Examples would be reliable information about products and their uses, frequent shopper rewards, and assistance in making choices. Essentially, many Web retailers will provide decision support systems for their customers. All this must be done in real time with responses returned to online customers in seconds, or better, milliseconds.

Models that operate behind the scenes—so-called "embedded" models—today make the marketing decisions involved in the millions of interactions and transactions in electronically mediated domains. These models have already demonstrated success in a growing number of business applications (e.g., promotion evaluation, coupon targeting, airline pricing, financial services, direct mail). Perhaps best described as half model, half process algorithm, these systems permit firms to realize the benefits inherent in the mass customization of marketing at lowest possible cost. We believe that they are forerunners in the wave of marketing decision automation.

An important factor that may drive acceptance of automation for individualized marketing is that the bulk of the decisions involved are ones that managers are unlikely to be interested in making. While one might anticipate resistance to the automation of some decisions managers now make today, we foresee rapid diffusion of automation in the customized marketing domain. As the proportion of commerce handled in this manner rises, the proportion of marketing decisions that are automated will also rise. We think this will lead to greater general acceptance of the concept and further diffusion in other areas.

Automation and the decision making environment

We have argued up to this point that a growing proportion of marketing decisions can be made not by manager but by machine. Underlying this general trend, however, will be significant differences in automation across different types of decision-making environments. We believe that there are two principle dimensions along which automation will vary (see Table 1). The first is the status of the product. This is a continuum ranging from existing products (i.e., well past introduction) to minor extensions (e.g., the proverbial "lemon-scented") to truly innovative (i.e., "really new"). The second dimension is the status of the product market on a continuum ranging from stable (e.g. mature) to trending (e.g., later growth or early decline) to turbulent (e.g., buffeted by exogenous shocks and rapid changes in tastes and/or technology). Table 1 presents a simple taxonomy of these environments, together with the potential level of automation.

Stable markets

For existing products in stable markets we foresee the possibility of near complete automation of marketing mix decision making in the long-run future. To be sure, automation will come first to short-run decisions (those made daily, weekly, monthly, or quarterly) and later to long-run decisions (those made annually or even less often). But we expect to see models handle decisions over increasingly long time horizons. Most of the modeling technology needed to automate price, promotion, advertising, and distribution decisions in these environments is well in hand and has been available for many years (e.g., Little 1975).

We anticipate that many reasonable managers might say, "Wait, won't there be some decisions, especially in advertising, for which a manager's judgment will always be required?" Models already address advertising *spending* decisions (e.g., the widespread availability of media allocation models) and we believe that they can also handle many things to do with advertising with the exception, of course, of making the ad itself (i.e.,

Table 1. Taxonomy of decision making environments and expected degree of future decision automation

		Product market		
		Stable	*Trending*	*Turbulent*
Product Status	*Existing*	Full Automation	Substantial Automation	Partial Automation
	Extension	Substantial Automation	Partial Automation	Limited Automation
	Innovation	Partial Automation	Limited Automation	Little Automation

copy creation will not be automated). For example, we expect that models can help guide the appeal to be used (e.g., Dowling and Kabanoff 1996) and how many creative executions to produce (e.g., Gross 1972).

Decisions regarding brand extensions in a stable market also may be substantially automated. The modeling infrastructure to automate much of this process is in place. Pre-test market evaluation systems for packaged goods are extremely well developed (e.g., Silk and Urban 1978) and are also available for durables (e.g., Urban, Hauser, and Roberts 1990). More recently, Fader and Hardie (1996) show how new product opportunities involving changes in levels for existing attributes (i.e., a typical line extension) may be identified and their prospects quantified entirely from scanner panel data. This approach has already been applied to dozens of markets by Information Resources, Inc. (Bucklin and Gupta 1997). If not the decision, then at least the process can be effectively automated.

Decisions regarding innovative products in stable markets (i.e., those introducing new benefits versus the current mix of existing benefits) may be partly automated in the future. In this setting, we see the key barrier to higher levels of automation as the inherent limitations in assessing and forecasting customer and competitor reaction to the introduction of truly new benefits. The problem is a lack of historical data or, alternatively, models that have been calibrated to forecast sales from basic customer needs and product attributes. Of course, the manager shares these problems with models. Some decisions, however, may be automated, especially those involving elements of the marketing mix that do not interact with the new product benefit. The technology in pre-test market modeling can also be put to use. A potential limitation is that new benefits often expand category demand (i.e., trending markets) while these models have traditionally emphasized forecasts of market share. Nevertheless, survey or experimental methods that account for potential demand expansion may help overcome this and provide the basis for partial automation (e.g., Mason 1990). Finally, data from analogous markets can provide benchmarks and upper and lower bounds for forecasts (e.g., Sultan, Farley, and Lehmann 1990, Bayus 1993).

Turbulent markets

The potential for partial automation narrows when both the market is turbulent and the product in question offers distinctly new benefits (i.e., is innovative). The ability of historical information to provide the basis for good forecasts drops significantly when market conditions are turbulent. This severely limits the degree to which marketing decision-making can be automated, even when the decisions pertain to an existing or well established product. Nevertheless, some aspects of decision-making in these environments will benefit from partial automation.

Two factors underlie our optimism. First, in turbulent market situations management attention needs to be focused upon the strategic and tactical matters in which the firm has influence over outcomes. Models can play an important role in keeping management attention directed towards these activities. Second, turbulent markets are seldom turbulent in every respect. For example, rapid changes in customer preferences may introduce chaos into product and pricing strategy, but they need not imply changes in distribution policies. Thus, if stable dimensions of the business situation exist along with turbulent dimensions, an automation opportunity still presents itself.

Incorporating competitive dynamics

Successful decision automation—especially full automation—will require that the relevant actions and reactions of competitors be incorporated into the modeling system. At first glance, building models to include competitive dynamics appears to be a daunting task and a potential Achilles' heel of decision automation. While many of the challenges of demand forecasting, marketing mix response, and objective function optimization have been overcome in data-rich environments with the application of sophisticated modeling technology and (effectively) unlimited computing power, most of this has been accomplished under often restrictive assumptions about competition.

There are many situations in which competitive dynamics may be effectively irrelevant to the decision at hand. There is the occasional case of pure monopoly, of course (e.g., due to patent protections or other proprietary knowhow or technology). But even when competition clearly exists, competitors' actions often have only small effects on the sales of other firms, when considered individually (e.g., markets which economists characterize as "monopolistically competitive"). Thus, the task of handling competitive dynamics should begin by focusing primarily on those competitors that have meaningful cross elasticities with the product in question. Even in seemingly competitive product categories, often there are only one or two other competitors whose actions significantly affect sales volumes (e.g., Bucklin and Gupta 1997). This suggests that it is important for management to remain focused on demand and avoid being unduly distracted by competition.

One particularly promising approach is the empirical reaction function (e.g., Bresnahan 1997, Leeflang and Wittink 1996). Marketing actions taken by the firm affect both customers and competitors. Actions that affect competitors may (or may not) induce potential reactions. The net effect of both customer response and competitors' reactions (if any) is captured in the market results that the firm observes. Calibrating an empirical reaction function over the time window that matches the decision horizon therefore provides a natural and straightforward way of incorporating competitive dynamics. This approach offers an excellent way for automated decision systems to handle competitive dynamics because it is driven entirely by the data and therefore avoids many of the assumptions that other approaches make (e.g., game theoretic analyses).

One limitation of empirical reaction functions is the requirement for potentially extensive historical information. To accommodate long time horizons and/or long lag times in competitive reaction, consistent data must be available for many years. Fortunately, this is increasingly less of a problem as data banks have begun to accumulate consistent records for long time periods. In the academic literature, two recent examples are the data sets used in the empirical studies by Dekimpe and Hanssens (1995) and Mela, Gupta and Lehmann (1997). Companies and market research suppliers are also keeping data longer—and preserving quick access to it—thanks to steep declines in the costs of on-line information storage.

Another approach to incorporating competitive dynamics is sensitivity analysis. This approach should be particularly useful for stable markets where there are problems with the availability or consistency of historical data (precluding the calibration of empirical reaction functions). As part of a decision support system for long-term promotion planning, Silva-Risso, Bucklin and Morrison (1997) tested the robustness of the profitability of model-generated promotional calendars to simulated changes in the timing and depth of competitors' promotions. Although the product category involved had extensive promotional activity and brand switching, there actually turned out to be very little impact of changes in competitor promotions on the best course of action for the target firm. While this is unlikely to be generally the case, it reinforces the notion that competition need not always be a critical factor in marketing decision-making and that management, first and foremost, should remain focused on its own demand.

Sensitivity analysis is likely to be of more limited value if the decision-making environment involves either turbulent markets or new products. In contrast to the case of tactical sales promotions, it becomes difficult for simulation to cover the full range of potential competitive reaction to an innovative product or in turbulent market situations. In these instances, we envision that decision systems will incorporate competitive dynamics in at least three other ways.

The first of these is capabilities analysis (e.g., Rothschild 1979). This assumes that managers will do what they can do and therefore provides a prediction of future behavior. The second is scenario analysis (Schoemaker 1995; Schwartz 1991). This approach implicitly relies on behavior patterns in other (hopefully similar) markets. (Although not necessarily equally weighted, these behavior patterns should, on average, form a prediction in the spirit of Empirical Bayesian analysis.) The third approach is game theoretic analysis (e.g., Rasmusen 1994). This assumes, of course, that game theoretic analysis can make sufficiently realistic assumptions so that managers will actually tend to do what they "should" do. When this is so, the prescriptions of game theory become a predictor of what competitors will do. The use of each of these approaches necessarily implies a lower level of potential decision automation, consistent with the taxonomy presented in Table 1.

Help wanted: Marketing engineers

The primary purpose of this paper is to articulate a long-term vision for decision-making in marketing. While we have made essentially a normative argument thus far, we are also mindful that building the road from decision support to decision automation will pose some formidable engineering challenges. Indeed, in order to achieve the benefits of automation, firms will need to invest in the development, testing, and refinement of model-based decision making. The up-front costs of this can be substantial. For example, one packaged goods firm recently spent more than one million dollars in development costs for a decision *support* system—not automation—for its salesforce to use in trade promotion.

Development costs aside, there are many additional challenges that marketing will need to overcome to build good decision automation systems. Often, managers pursue sales or share as short-run marketing objectives, paying less attention to profitability. Building decision automation based on profit maximization may require re-engineering parts of existing systems. For example, widely used tools for promotion evaluation based on store-level data (e.g., Abraham and Lodish 1987, 1993) work well when the objective is to increase short-run sales. They break down, however, when the objective is to maximize profitability (because they do not decompose the sales bump into borrowed versus incremental units). This can require engineering a new modeling infrastructure based on panel data (e.g., Silva-Risso, Bucklin and Morrison 1997).

Focusing on profits also requires accurate information on costs. Marketing managers who have historically focused on sales and market share may pay little attention to costs, or be satisfied with rough approximations. Marketing engineers building decision automation systems will need to link marketing decision systems with accurate, up-to-date information on costs.

Finally, decision systems will need to be able to produce results in which large numbers of control variables are simultaneously involved. Consider the problem in price promotions for packaged goods studied by Silva-Risso, Bucklin and Morrison (1997). Simply to plan a 52-week price promotion calendar for one item involves an enormous number of discrete decisions (a 0/1 on-or-off promotion decision for each week plus a discount depth for each week that a promotion is on). Insuring that models deliver global maxima in complex cases like these will require adapting state-of-the-art advances in optimization algorithms into decision support and automation systems.

Conclusion

In this paper we have advanced the proposition that much of marketing decision-making will be automated in the future. Decision automation is likely to grow because firms will pursue the productivity gains it offers, because models will make better decisions than managers in many instances, and because the decisions involved in marketing at the individual level will be too numerous, detailed, and frequent to warrant the day-to-day involvement of managers. Decision automation in marketing, however, will be contingent upon the decision-making environment and far from a universal phenomenon. We may come close to full automation of decisions regarding existing products in stable markets. We will make the least progress in chaotic markets where the product is innovative.

We foresee that decision systems will account for the actions and reactions of competitors using a variety of different approaches. Empirical reaction functions will be widely used in cases where historical data is extensive and consistently available over long time horizons. Sensitivity analyses will be useful in stable market situations. Finally, game theoretic analyses, capabilities analyses, and scenario analyses based on analogous markets will be components of decision systems in unstable market situations and for decisions involving innovative new products.

Over time, accumulated knowledge provides better prior predictions of the impact of various actions. These empirical generalizations provide at least a basis for a default decision. Indeed, "management by meta-analysis" provides a reasonable standard for evaluating marketing decisions.

One corollary to this argument is that the marketing manager's locus of decision making will change. This means that certain decisions may be removed from their control. This, of course, may sometimes be difficult to sell to incumbents and may require a change in their incentives. It will also require the new role of supervising and updating the automated systems. In a sense, managers may become analogous to pilots of Boeing 777's, mostly making minor alterations to course but available in the event the market turns turbulent.

Twenty years ago, Little (1979) posed the question: whither decision support? In light of the foregoing, we now pose the question: whither the marketing manager? What will be his or her role in a function where more and more decisions can be made by machine? Our vision for 2020 is decidedly optimistic. We foresee a "utopia" in which marketing managers focus on long-run and strategic issues. The emphasis will shift from which mix decision to make to how to design and improve the models that make such decisions. Indeed, most of the time and energy of tomorrow's marketing manager will go toward making decisions where, to adapt a popular phrase, no model has gone before.

Acknowledgment

The authors thank the editor, an anonymous reviewer, and participants of the Conference on Competitive Decision Making, Charleston, SC, June 1997 and the Third Invitational Choice Symposium, Columbia University, June 1996, for their helpful comments and ideas.

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