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Broadening the perspective on marketing decision models

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Abstract

Marketing models are of invaluable importance for the advancement of marketing science. Regarding the role of models in marketing decision-making in practice we question the claim that marketing models are routinely used by many companies. Marketing models are suitable for certain types of marketing decision situations but much less for others. We advocate the development of integrated marketing management support systems (MMSSs), in which the strong points of marketing models are combined with the strengths of other types of MMSSs.

Keywords: Marketing decision models; Marketing management support systems; Success metrics; Decision automation

1. Introduction

Marketing models have been of great value for the accumulation of generalizable marketing knowledge. The advancement of marketing science has been the purpose of the development of many "descriptive" marketing models (Lilien et al., 1992; Eliashberg and Lilien, 1993). For example, meta-analyses in which results from different studies on a specific marketing topic (e.g., the effect of advertising) are reviewed and integrated are typically based on model-based analyses of empirical data (see, for example, the Special Issue of *Marketing Science* on empirical generalizations; Bass and Wind, 1995). It is difficult to imagine how the body-of-knowledge of marketing could have grown and will further grow without the use of increasingly advanced marketing models. In the end, the results of research in marketing science, i.e., insights in marketing processes, can be used to support marketing decision making in companies.

Besides being useful for the development of marketing theory and thus indirectly for the support of marketers, (predictive and normative) marketing models also aim at directly supporting their decision-making processes. In the review article of Leeflang and Wittink (2000) the authors pose that at many firms managers now routinely use model-based results for marketing decisions and they expect this to further increase. A continuing improvement of the quality of models will be the major driver behind this. Increases in data availability and the sophistication of model-building methods will further fuel the model quality leap. Ultimately, decision automation could become feasible in various marketing decision situations.

Leeflang and Wittink (2000) (see also Leeflang et al., 2000) give a very interesting account of the state-of-the art with respect to marketing models and

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their use for decision making. In this contribution we aim at broadening the perspective on marketing decision models in a number of ways. First, Leeflang and Wittink (2000) are rather optimistic about the actual use and success of models for the support of marketing decision making. However, in many situations marketing models have not been so successful, and we, therefore, pay attention to the perspective of model use and model success. In doing so we also deal with the issue of the measurement of model success. Second, we put marketing models into the broader perspective of marketing management support systems (MMSSs). Marketing models represent one particular type of MMSSs, and we will discuss the issue when marketing models are the most appropriate decision aid and when other types of MMSSs will be more suitable. This implies broadening the Leeflang and Wittink (2000) perspective in paying attention to the demand-side of marketing decision making and the match between this demand-side and the supply-side of successful decision support. Third, developing a demand-side perspective calls for explicit attention for the role of the marketer. We discuss the perspective for the marketer in a world with an increasing use of marketing models and other types of MMSSs. Will the marketer be replaced by automated systems? Finally, we pay attention to the perspective for marketing models in future MMSSs.

We limit this contribution to marketing decision models as Leeflang and Wittink (2000) discuss them. These models are meant to provide direct decision support to marketers by relating marketing efforts to results in the market. We acknowledge the importance and value of other types of analytical techniques such as factor analysis and conjoint analysis for analyzing (market research) data in business. However, these techniques are outside the scope of this paper. While these techniques evidently are model-based, we would not call them *decision* models.

2. The perspective of model use and success

Different operationalizations of model success exist (Wierenga et al., 1999). The first level of success is *technical validity*. This is the extent to which the system is a valid representation of the marketing process and makes statistically accurate predictions. Model builders tend to be especially interested in this dimension of model success. However, technical validity is a necessary but not sufficient condition for managerial model use and success. A second set of model-success variables refers to the subjective evaluation of success by their users. *User impact* variables such as user satisfaction and perceived usefulness are examples of these variables. Objective success variables are *organizational impact* measures such as profit, sales, and market share. These are they type of measures based on which, ultimately, the success of models will be judged. It is neither easy nor always possible to estimate the effects of marketing models on these criteria and sometimes more simple, *individual*, performance measures are used instead. Examples are time saved and increased personal productivity. The impact of a model on an individual user does not necessarily coincide with its impact on an organization.

With respect to the success of marketing models, Leeflang and Wittink (2000), abstract) write that "at many firms managers now routinely use model-based results for marketing decisions." They also suggest that these managers are quite successful in doing so. We question the validity of this claim. We observe that compared to the work put into the development of marketing models, the research efforts spent to investigate their applications and impact have been relatively modest and that the research that has been conducted does not lead to unanimous results. For the new product market simulation ASSESSOR the number of applications is reported to be over 6000 (Little et al., 1994) and the SCAN * PRO system that estimates the effects of sales promotions has been used in practical applications more than 500 times (Parsons et al., 1994). However, several authors, especially in the context of OR-based marketing models, have expressed pessimistic views on the use of marketing models in the marketing practice. "Even several decades after the earliest operational marketing models were first introduced, their impact on practice remains far below its potential," (Eliashberg and Lilien, 1993, p. 19) and "the practical significance of marketing science has remained very limited" (Simon, 1994, p. 40).

Our own (not representative) interaction with marketers also supports the view that we should be careful not to overestimate the actual usage rate of marketing models in companies. The so-called descriptive marketing models are applied on an ad-hoc basis by organizations to obtain insights in, for example, the effectiveness of marketing instruments or the impact of competitive behavior. However, the support not to mention the replacement of marketers in the process of making tactical and strategic marketing decisions does not seem to take place on a large scale yet. Because of the availability of continuous data collected by companies like IRI and AC Nielsen the situation in FMCG markets favors the development and use of such models. However, even here we doubt that model use is really widespread and the situation in these markets is certainly not representative for marketing practice in general. In this respect marketing scientists, like marketers, should be aware of the risks of biased judgments about the usage rate of the models they produce. The risk of such biases may result from close cooperation with model using companies or data suppliers in market situations that are not representative for most markets. Despite the progress being made on the supply-side (Brand and Leeflang, 1994), for example, in business-to-business markets many marketers still use only judgment to support their decisions.

When we look at the *effects* of model use, research also shows mixed results. Successful implementations have been reported (e.g., Fudge and Lodish, 1977; Lodish et al., 1988). However, the results of several laboratory experiments are not unequivocal. In an experimental study the use of a model for determining the size of the advertising budget (ADBUDG) negatively affected decision quality (Chakravarti et al., 1979) whereas in another experiment the same type of model had a *positive* effect on the quality of decision making (McIntyre, 1982). Mixed findings with respect to the impact of management support systems have also been reported in other management fields.

Based on published research, we conclude that, for certain decision situations, very successful marketing models have been developed. This is confirmed by the results of a survey among model builders (Wierenga and van Bruggen, 1997a, 2000). Decisions on sales force planning, media planning, shelf space allocation, and sales promotions planning appear to be well suited to be supported by models. Models developed for these tasks are frequently implemented and successfully used. However, there are also several models that were not very successful or that have not even been implemented at all. We propose that it is due to the fact that these models did not fit with the decision situation for which they were developed. Alternative types of MMSSs will be more effective in these situations.

3. The perspective of marketing models in the broader context of MMSSs

Marketing models represent one specific type of MMSSs. We now discuss the applicability and success of marketing models within the broader context of how to foster the success of MMSSs in general. In our opinion three key issues are important for MMSSs in order to be successful:

1. a demand-oriented approach towards the development and implementation of MMSSs;
2. a contingency-based assignment of MMSSs to a marketing problem situations (not every system is suitable for every marketing decision); and
3. awareness of factors beyond the systems itself, that are critical to the success of MMSS.

3.1. Demand-oriented approach

Marketing decision aids can only be effective if they match with the thinking and reasoning processes of the marketers that are supposed to use them. The development of MMSSs over time has been more supply-side than demand-side-driven. In a sense an implicit assumption seems to have existed that technically sound models would be automatically useful. For example, Leeflang and Wittink (2000) show that the availability of operations research techniques, such as mathematical programming, made a strong imprint on the developments in the first era of marketing models (1950–65). Examples of drivers on the supply-side of MMSSs in later periods were econometrics and multivariate statistics, expert systems technology, and information and

communication technology. To make these technologies contribute to the solution of marketing problems in companies, the decision maker should perceive them as being useful.

The decision-maker perspective is almost completely lacking in the Leeflang and Wittink (2000) article, but the same is also true in the marketing model literature at large. Leeflang and Wittink (2000) present a (normative) stages framework of the model-building process, running from *opportunity identification*, through stages such as *specification* and *parameterization* (estimation) to *use* and *updating*. It is often assumed that managerial decision making also follows such a sequence of steps: problem recognition, identifying alternatives, choosing the best one, and evaluating the outcome. However, Weick (1983) suggests that these step-like models may have erroneously been inspired by how scientists think, and that, in reality, managerial decisions are made in a more holistic way. Weiss (1980) even denies the existence of decision-making processes on the part of the manager at all.

We know very little of how marketers make decisions. The marketing management literature abounds in recommendations of how marketing managers *should* make decisions, while there is only a very limited literature about the way marketing decision makers actually make decisions. Examples of such studies are those of Howard and Morgenroth (1968) who discuss pricing decisions in oligopolistic markets, Hulbert (1981) who reviews descriptive models of marketing decisions, and Goldstein (1993) who describes the way product managers learn from scanner data. We acknowledge that it is more complex to study managers than consumers, but the payoffs from such studies could be great. Examples of important questions are: how are marketing problems recognized and formulated; how does information acquisition and processing take place; what is the role of variables such as cognitive style, expertise, and experience; what is the role of time pressure; and how are marketing decision processes affected by the use of MMSSs?

Knowledge about the demand-side of decision making will help to obtain a better fit with the supply-side of decision support tools. For example, under certain conditions, marketing models can be very effective tools to improve the outcomes of marketing decisions while under other conditions they are probably not. We elaborate on this issue in Section 3.2.

3.2. Contingency of the MMSS upon the marketing decision situation

For a demand-driven approach to MMSSs, we need a typology of the different ways marketing problems are solved by marketers. Wierenga and Van Bruggen (1997b, 2000) developed the ORAC model in which four different marketing problem-solving modes are distinguished: Optimizing, Reasoning, Analogizing, and Creating.

In the *optimizing* mode, the marketer searches for the best (optimal) solution. In the *reasoning* mode, the marketer uses a mental model for reasoning about the problem. *Analogizing* means that the marketer, when confronted with a problem, searches his/her memory for a similar problem and takes the solution of this previous problem as the starting point for solving the case at hand. In the *creating* mode, the marketer searches for novel and effective ideas by means of transforming and enlarging the problem's conceptual space and divergent thinking.

Three groups of factors determine which mode occurs in a particular decision situation. These are *problem characteristics*, *decision environment characteristics*, and *decision maker characteristics* (Wierenga and van Bruggen, 1997a,b). For example, if the problem is highly structured and there is much data (decision problem characteristics), if the market is stable and there is an ample time frame (decision environment characteristics) and the decision maker has an analytical cognitive style (decision maker characteristic) there is a high probability that the optimizing mode will be employed.

Marketing models match best with the optimizing mode and will thus be most effective in an optimizing situation. It is easy to think of marketing decision situations where the conditions for optimizing apply (e.g., sales call planning, media planning, sales promotions, and new product decisions in FMCG). Very successful applications of marketing models for supporting these types of decisions have been reported (Parsons et al., 1994). However, optimizing is probably not the most frequently occurring mode through which marketers solve problems. If one asks participants in seminars and executive courses (academics

as well as practitioners), as we have done several times, one typically obtains the following distribution of marketing decision situations over the four marketing problem-solving modes (rounded-off numbers): Optimizing 10%; Reasoning 40%; Analogizing 40%; and Creating 10%. Marketing decision making is thus thought to primarily be a matter of reasoning and analogizing, much more than of optimizing or creating. We think that these figures show considerable face validity. Goldstein (1993), who observed how product managers in FMCG industries deal with scanner data, found that even in such data-rich environments, the dominant modes were *reasoning* (where the mental model of the manager plays an important role), and *analogizing* (building stories about events and retain these in memory). This might explain why the use and impact of marketing models has systematically remained under the expectations. For many marketing problems, other types of MMSSs will be more appropriate than marketing models are.

The reputation of marketing models may have been harmed because people have tried to use them for decision support in situations with a low fit with the decision situation. Wierenga and van Bruggen (1997a, 2000) carried out a study among 38 developers of MMSSs in which they collected information about the type of MMSSs, the characteristics of the problems for which the MMSSs were developed, and about the impact and success of these systems. It turned out that the majority of the systems (21 out of 38) were supporting the optimizing mode, whereas in terms of the characteristics of the decision situations, only a minority (7 out of 38) required an optimizing system. For 14 $(=21-7)$ systems, a discrepancy existed between the demand for and supply of MMSSs. An MMSS supporting one of the other modes would have had a better fit. In the same study, systems with a good fit between the demand-side and the supply-side were more successful. They were implemented in more companies, had a higher endurance rate, and generated more user satisfaction. Therefore, we conclude that marketing models can be effective decision support tools, as long as they are applied to the right tasks. If the decision situations does not ask for a marketing models, applying marketing models will probably be less successful than applying alternative types of MMSSs.

3.3. Alternative MMSSs

Marketing models are a specific type from a much larger set of MMSSs (Wierenga and van Bruggen, 2000). Eight different types of systems can be distinguished. We describe them in Table 1. The first three types of systems are *data-driven* MMSSs, the last five represent the class of the (more recently developed) *knowledge-driven* MMSSs.

The various MMSSs match with different specific marketing problem-solving modes. Marketing models and marketing expert systems aim at finding the best decision and are thus best suitable for the *optimizing mode*. For the *reasoning mode*, marketing information systems, marketing decision support systems, and marketing neural nets can help to develop and adapt the mental models of decision makers about their markets. Marketing knowledge-based systems can be used to reason with these mental models. Marketing case-based reasoning systems support the *analogizing* mode and marketing creativity support systems the *creating* mode. Wierenga and van Bruggen (2000) provide a more extensive discussion on how to determine the most suitable MMSS for a particular problem situation. Selecting a decision aid contingent on the characteristics of the marketing problem situation will greatly increase the success of MMSSs.

3.4. Factors beyond the system characteristics that determine the success of an MMSS

So far, we have emphasized the match between the demand-side and the supply-side of an MMSS as an important determinant of its success. Factors beyond the system itself can play an important role too. Wierenga et al. (1999) have developed a framework of the factors that determine the success of MMSSs. Apart from the demand- and supply-side factors described above, important elements in this framework are design characteristics, characteristics of the implementation process, and the distinction between different success indicators of MMSSs.

Examples of *design* variables of an MMSS are accessibility of the system, integration with other systems, adaptability and flexibility of the system, and quality of the user interface. Critical elements of the *implementation process* are user involvement

Table 1
Eight different types of marketing management support systems (from Wierenga and van Bruggen, 2000)

1. *Marketing models* consist of mathematical representations of marketing problems that aim at finding optimal values for marketing instruments. The philosophy underlying these systems is that it is possible to find an objective best solution.
2. *Marketing information systems* aim at the storage, retrieval, and (statistical) analysis of data. By means of manipulating quantitative information, marketing information systems assist marketers in analyzing what has happened in the market and determining possible causes of events.
3. *Marketing decision support systems* provide marketers with the opportunity to answer "what-if" questions by means of making simulations. Marketing decision support systems put a large weight on the judgment of the decision maker, rather than on searching for the optimal (best) solution.
4. *Marketing expert systems* capture the knowledge from a marketing expert in a specific domain and make this knowledge available in a computer program for solving problems in the domain. Like marketing models, expert systems take a normative approach in searching for the best solution for a given problem.
5. *Marketing knowledge-based systems* describe a broader class of systems than marketing expert systems. They obtain their knowledge from any source, not just from human experts but also from textbooks, cases, and so on and can use a wide range of knowledge representations methods. Unlike marketing expert systems, marketing knowledge-based systems do not focus on finding a best solution but emphasize the reasoning processes of decision makers.
6. *Marketing case-based reasoning systems* focus on the support of reasoning by analogies. Analogous thinking is a way of solving problems in which solutions to similar past problems are taken as a starting point for solving a current problem. Marketing case-based reasoning systems make cases available in a case library and provide tools for accessing them.
7. *Marketing neural networks* are systems that model the way human beings attach meaning to a set of incoming stimuli, that is, how people recognize patterns from signals. Based on this principle, a large supply of algorithms is available now that we can recognize patterns in data.
8. *Marketing creativity support systems* are computer programs that stimulate and endorse the creativity of marketing decision makers.

during the development and implementation of the system, top management support, presence of an MMSS champion and a cooperative attitude of the IS department (Wierenga and Oude Ophuis, 1997). An excellent marketing model that has a perfect fit with the decision situation can fail if something is wrong with one or more of the design or implementation factors (e.g., the system is not integrated with an often-used data system, or the IS department is boycotting the system). The various drivers of MMSS success are likely to interact. For example, a high-quality marketing model will be especially effective if is it used by a skillful marketer and if it has a user friendly design and is implemented carefully. In the hands of a less qualified marketer the same model will not be able to deliver its full potential.[2]

In summary, we see that different measures for the success of MMSSs exist. From a decision support perspective, technical validity is a necessary but not sufficient condition for impact on decision-making processes. To make systems effective, they should match with the demands of the decision situation. To obtain such a match, various types of MMSSs are available. Marketing models represent just one of these types.

4. The perspective for the marketer when MMSSs are increasingly being used

The developments with respect to the development of MMSSs sometimes make people raise the idea that for certain decision situations a future without a role for the marketer might exist. Leeflang and Wittink (2000, Section 3.2) also describe a shift in emphasis from descriptive to predictive and normative models and seem to foresee decision automation in fields where models provide superior marketing decisions. This would especially be the case for so-called repetitive decisions. This picture of the future builds on the arguments as put forward by Bucklin et al. (1998) and on the fact that sophisticated model-building procedures allow for this.

We acknowledge that due to, for example, the data explosions in some fields it will be increasingly difficult for human decision makers to make all the

[2] We thank one of the anonymous reviewers for bringing up this point.

decisions that need to be made. This is particularly the case for very operational marketing activities. For example, the design of tailor-made sales promotions in web-based environments cannot be done by humans if hundreds of thousands (potential) customers visit a virtual store that operates for 24 hours a day. We also acknowledge that if a model makes decisions that a manager used to make this will create alternative opportunities to use these managerial resources. However, we oppose the idea that decision automation leads to improved performance especially with respect to tactical and strategic marketing decisions.

The argument in favor of decision automation builds on the notion of human's cognitive limitations in information acquisition and processing (Simon, 1957; Hogarth and Makridakis, 1981). Human decision-making processes may become biased, especially in complex environments. Information overload or increased time pressure can, for example, cause this complexity. These two conditions are not unusual in many markets of today. Research by (Blattberg and Hoch, 1990; Hoch and Schkade, 1996; Van Bruggen et al., 1998) shows that by providing decision makers with models one can reduce these biases and thereby improve decision performance. However, this finding should not lead to the thesis that models are even better than managers and that it would thus be worthwhile to replace managers by models. Advocates of the latter argument find support in the work of Meehl (1954) and in follow-up research. He argues that many judgments are best made statistically, not intuitively. However, using Meehl's work to bypass managers by models passes over the strengths of human decision makers and especially those of experts. One can also question the ecological validity of this type of research favoring models over managers because they may not represent the majority of situations and tasks a manager faces (Jungermann, 1983). Studies have shown that statistical models can outperform human prediction (Clark, 1992) even when the model is largely based on the behavior of the human expert (Dawes and Corrigan, 1974). This is the case in decision situations where forecasts have to be made based on multiple (given) cues. However, predicting from multiple cues is only one role performed by human experts. They must also formulate hypotheses, adjust these in the light of new data, avoid catastrophes and communicate ideas (Clark, 1992). Shanteau (1988) observes that experts have extensive and up-to-date content knowledge, have highly developed perceptual and attentional abilities, have a sense of what is relevant in making decisions (leading to more selective information search behavior), are able to simplify complex problems, and are able and willing to adapt their decision strategies to changing task conditions. Spence and Brucks (1997) find that expertise does especially well in less-structured situations. These are the situations were models may not do as well and where decision automation is not likely (Bucklin et al., 1998). Furthermore, we also add creativity as a superior characteristic of human decision makers.

Therefore, it is the *combination* of model and manager that makes the difference with either the model or the manager alone. Where humans are weak models may do well. However, the other way around humans will do well where models are not as good. Blattberg and Hoch (1990, p. 890) describe the strengths of experts relative to models. Models depend on experts in that they only know what the model builder has told them. Experts know what questions to ask, can identify new variables and are able to predict *and* diagnose. Experts can judge variables that are difficult to measure objectively. Finally, experts are able to recognize and interpret abnormal cases containing "broken leg" cues, which are highly diagnostic but so rare that they are not included in a model.

Finally, decision automation increases the risk of too much convergent and too little divergent thinking. This will reduce the opportunities for really creative (out-of-the-box) solutions to problems. Bucklin et al. (1998) assign especially decisions on existing products in stable markets to be suitable for automation. This assumes that the marketer should leave things as they are and approach problems as they are presented. Opposite to this a marketer could probably become much more successful by not taking a decision situation for granted and automate responses but by exploring and transforming the conceptual space and expanding the number of possible solutions through divergent thinking. By doing so and restructuring the whole decision situation, John Sculley, for example, was able to create a

strong competitive position for Pepsi Cola next to Coca Cola (Russo and Schoemaker, 1990).

Repetitiveness will sometimes create a need for decision automation. However, repetitiveness as such should not be the reason for decision automation. Repetitiveness will create opportunities to use feedback information, learn and develop knowledge. Managers will be able to apply this knowledge and it can also be built into models, which will enhance their quality. However, this does not mean that a model alone will outperform the *combination* of model and manager. We propose that in making decisions a (good) marketer will always add value to model-based recommendations. As Simon (1987, p. 63) wrote: "the effective manager does not have the luxury of choosing between 'analytic' (which can be model-aided) and 'intuitive' approaches to problems. Behaving like a manager means having command of a whole range of management skills and applying them as they become appropriate."

We stress that no unconditional hierarchy in the different ways of approaching problems exists. This means that using managerial judgment as the most important basis for marketing decisions is not always inferior to developing optimal decisions using model-based analyses. Real intelligent decision making will be the result of a trade-off between the amount of cognitive effort one is able to spend and the decision accuracy one wants to aim for (Payne et al., 1993). If there is ample time for making decisions than it makes sense to spend a lot of effort and use MMSSs to develop decisions that are as accurate as possible. However, high time pressure quickly deciding by carefully applying managerial heuristics instead of performing extensive model analyses may be equally or even more effective.

5. The perspective for marketing models in future MMSSs

The most important characteristic of the marketing management environment of the future is the enormous supply of data. These data offer great opportunities to develop information and build innovative marketing programs. However, while the volume of available data has grown exponentially, the human brain has not advanced in any comparable way to process and interpret this data (Simon, 1997). Furthermore, most competitors have access to the same data. Therefore, future competitive advantage will not be derived so much from having lots of data, but from having the right MMSSs to transform the data into actionable marketing knowledge.

Although the availability of data is a favorable condition for the development and use of marketing models, we are not sure that the bulk of the growth will be in the direction of classical econometric marketing models. The enormous databases and data warehouses that companies have might as well create a demand for neural networks and other data-mining techniques. Data mining is the process of exploration and analysis of large quantities of data in order to discover meaningful patterns and rules (Berry and Linoff, 1997). Data mining is an adaptive, learning technique, that starts from the data, whereas (econometric) modeling as described by Leeflang and Wittink (2000), usually starts with the specification of a model on the basis of theory. It can be especially productive to combine new and traditional approaches. Cooper and Giuffrida (2000), for example, combine the development of a traditional market-response model with data mining techniques to develop an effective sales promotion support tool.

5.1. Towards integrated MMSSs

Due to the developments in cognitive science and artificial intelligence the possibilities for representing (qualitative) knowledge in computers systems and making these systems reason with this knowledge have quickly increased. The automated analysis of scanner data (Schmitz, 1994) is an early example of this approach in marketing. The possibilities for dealing with knowledge in computers open the way for *integrated* MMSSs that carry out both qualitative reasoning and quantitative data analysis. Earlier in this paper we described eight different types of MMSSs. Ideally, in the future we will not see "stand-alone" systems, that are either econometric models or expert systems, but systems that integrate the different technologies in order to deliver the best possible support to the decision maker. The same marketer, at one time may need a data-mining tool to analyze a large data base, while at another time, may want to consult a case-base with earlier sales promo-

tions to get inspiration for a new sales promotion campaign. In some instances a sophisticated econometric model for the analysis of sales promotion data from a scanner panel may also be needed. MMSSs of the future combine these different features in one system, where the user can invoke the desired type of support through a user-friendly central control device. In such systems the maximum synergy can be created between marketing models and other support technologies. All of these technologies share a common ground in that they are especially effective if they support rather than replace decision makers. From a decision support perspective, advances in marketing modeling are thus great and promising because they strengthen the combination of system and manager. Making the mistake of wanting to replace the manager by models would seriously hamper the impact of advanced modeling approaches on decision making.

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