The Success of Marketing Management Support Systems

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Abstract
This paper provides an introduction to this Special Issue by a) providing a framework for evaluating the potential and actual success of marketing management support systems (MMSS), and b) briefly discussing how each paper in this Special Issue addresses the general topic of managerial decision making. The paper concludes by outlining some key questions that still need to be addressed.
(*Measures of Success*; *Decision Aids*; *Managerial Decision Making*)

Introduction
This issue of *Marketing Science* is about managerial decision making; how marketing managers now go about making decisions and the description of a number of new decision aids that support marketing managers in the preparation, execution, and evaluation of marketing activities. The purpose of this opening article is to provide a framework for evaluating these decision aids and providing a better understanding of the interaction of these aids with the marketing manager. We then use this framework to briefly discuss how each of the papers in this issue addresses the general topic of managerial decision making and lay out possible future research agendas.

Decision aids have been a central activity of marketing scientists for over 30 years. Initial efforts centered on building complex models that often looked for an optimal solution. Prototypical models of this type were MEDIAC (Little and Lodish 1969) and SPRINTER (Urban 1970). In 1970, John Little introduced the concept of a simple, but robust marketing model that usually required judgmental input from the manager. He coined the term *decision calculus models* for such an approach. Subsequently, we find the introduction of *marketing information systems* (Kotler 1966; Amstutz 1969), *marketing decision support systems* (Little 1979) such as ASSESSOR (Silk and Urban 1978), *marketing expert systems* such as ADCAD (Burke et al. 1990), and most recently, *marketing case-based reasoning systems* such as ADDUCE (Burke 1991). We use the term *marketing management support systems* (MMSS) to refer to this whole set of tools. Many of these tools have now become available for direct use in real world situations (Lilien and Rangaswamy 1998).

Given this long history of development, it is somewhat surprising that there are few studies that investigate the impact of these models on the decision making of the manager and firm. One notable exception is the work of Fudge and Lodish (1977) who used a field study to document the impact of the CALLPLAN model (Lodish 1971). They did this by comparing sales generated by one set of sales people using CALLPLAN to another group using their habitual planning methods. They found that use of the model led to increased sales. Other examples of field studies can be found in Lodish et al. (1988) and Gensch et al. (1990). Interestingly, management did not completely carry out the major reallocation of resources to products and markets as was recommended by the model proposed by Lodish et al. (1988) even though this study showed positive impact. In contrast, the Gensch et al. model (1990) was implemented company-wide after the field study showed improved firm performance due to the

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model. According to the authors, one of the key factors for the success of the MMSS was the direct involvement of the company's CEO in the development and implementation of the decision aid.

The above referenced studies deal with the use of MMSS for *real-life* decision making in companies. However, most of the empirical studies designed to test the efficacy of the MMSS have been conducted in laboratory settings. Chakravarti et al. (1979) carried out an experiment using practicing managers as subjects. They measured the effect of using the ADBUDG model (Little 1970) for supporting advertising decisions and found that use of the MMSS led to poorer decisions in terms of operating profit and prediction accuracy of market shares. McIntyre (1982) carried out a similar experiment, using the same type of MMSS, but found a positive effect of the use of the MMSS on profits. One of the major differences between the two experiments was that McIntyre used a setting where the underlying response function had no lagged effects, while in the Chakravarti et al. study the underlying response function was more complex, i.e., had a lagged term. It appears that managers were not able to estimate the true response in the latter case and this led to the poorer model results (Chakravarti et al. 1981).

Zinkhan et al. (1987) studied the effects of several decision-maker characteristics on the success of MMSS measured by use and satisfaction. They found that cognitive differentiation (a cognitive style variable) and prior involvement with decision support systems (an experience variable) were positively correlated to the use of an MMSS. Van Bruggen et al. (1998) carried out an experiment in the MARKSTRAT (Larréché and Gatignon 1990) environment. They found a positive effect of the use of MMSS on market share and profit. However, subjects using the MMSS did not report having more decision confidence than those not using the MMSS. Likewise, McIntyre (1982) found no relationship between objective results of the use of an MMSS and subjective variables as reported by the managers. In a recent study, Hansen and Staelin (1999) found that managers' confidence in their decision concerning the selection of an option among risky alternatives has more to do with their ability to take into account all the relevant factors affecting the choice than the decision rule they use based on these factors. We take these studies to indicate that managers' confidence in the decision taken has little relationship to veracity of the decision.

Hoch and Schkade (1996) studied the effect of the decision environment on the impact of MMSS. In their study subjects had to predict future credit ratings of applicants based on four financial characteristics of the applicant. In a predictable environment, historical cases and a pattern matching strategy turned out to offer adequate support to decision makers. However, in less-predictable (dynamic) environments, linear models were more effective decision aids. This finding indicates that the degree to which a decision support tool is effective may depend on the decision environment.

We draw several conclusions from these studies. First, there is substantial proof that MMSS can increase firm profit and other measures of performance. However, this success does not appear to be universal, but instead depends on the specific characteristics of the situation in which the system is used and specific success measure one is looking at. Second, there is still a need for further research that provides better insights in the conditions under which MMSS are successful. From the studies reviewed above several antecedents of MMSS success emerge such as support from top management, cognitive style and experience of the MMSS user, and fit of the MMSS with the decision environment. However, the interaction of these factors and the effects of other factors are still not well understood. Third, studies of this type used many different measures for the success. Examples include the extent to which the MMSS was actually used by decision makers, the effect of an MMSS on market share, profit, forecast accuracy, decision confidence, and the acceptance of the system's recommendations by management. In further work it is important to distinguish between different success measures, to examine their mutual relationships, and to be clear about which dependent variable(s) to include in empirical studies on the effects of an MMSS. In the next section we present a comprehensive framework of the factors that determine the success of an MMSS.

A Framework for the Success of Marketing Management Support Systems

We highlight five factors that determine the success of a marketing management support system. These are: (1) the *demand* for decision support (2) the *supply* of decision support (the decision support offered by the MMSS), (3) the *match* between demand and supply, (4) the *design characteristics* of the MMSS, and (5) the *characteristics of the implementation process* of the MMSS. Together with (6), the dependent variable *success* of the MMSS, these factors constitute the main building blocks of the framework presented in Figure 1.

We posit that the match between the demand side (the decision processes to be supported) and the supply side (the functionality of the management support systems employed) is the primary driver for the *potential* success of an MMSS. The extent to which this potential success will be actually realized depends on the *design characteristics* of the MMSS and the *characteristics of its implementation process* (Davis 1989, Alavi and Joachimsthaler 1992). Most of the factors in the framework are self-explanatory and we will highlight only a few elements here.

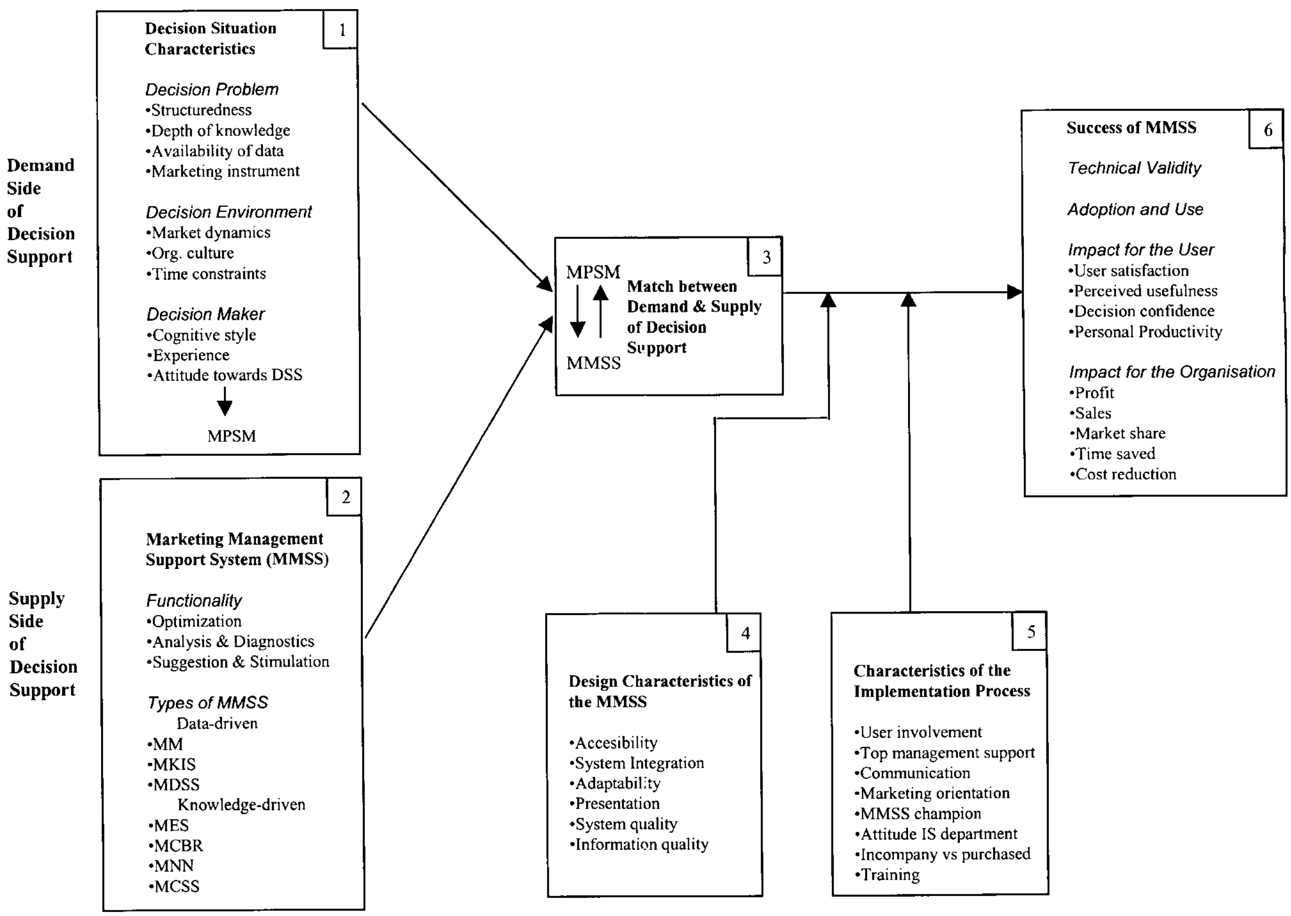
We start with the context of problem-solving activities of (marketing) decision makers, i.e., the *demand*-side of decision support (Figure 1, Box 1). The early writings in the decision support systems/information systems (DSS/IS) literature (Mason and Mitroff 1973, Mock 1973, Chervany et al. 1972; Lucas 1973) mentioned three basic factors that characterize the decision situation. These are (i) the *problem* that has to be solved, (ii) the *environment* in which the problem is solved, and (iii) the *decision maker* who has to solve the problem.

The problem being solved can be characterized by its degree of *structuredness*. Marketing problems vary enormously along this characteristic. Thus, sales-force allocation and media planning are examples of relatively structured problems, while designing a marketing communication or developing a marketing strategy are examples of less-structured problems. The decision-environment can be characterized by the level of *market dynamics*. When firms are operating in stable markets it is relatively easy to build mathematical models and perform some form of optimization. However, in turbulent markets decision makers are hard-pressed just to understand and interpret what's going on (Bucklin et al. 1998). Consequently, MMSS need to be adapted to reflect these less-structured conditions. Table 1 provides our characterization of the papers in this issue along these two dimensions. Interestingly, we find no papers addressing issues where there is low problem structure and the environment is turbulent. This is not surprising, since this situation is probably the most difficult to model. Still, it also points to the need for others to develop methods for providing help to managers in such situations.

A third factor that characterizes the decision situation is the decision maker's *cognitive style*, i.e., the process through which a (marketing) decision maker perceives and processes information. One common classification of this cognitive style is analytical decision making versus nonanalytical or heuristic decision making. It seems that an analytical cognitive style facilitates the use of MMSS (Larréché 1979, Zinkhan et al. 1987, Van Bruggen et al. 1998). However, Benbasat and Dexter (1982, 1985) found that especially low-analytical decision makers have the most to gain from decision support aids if they actually use them. Van Bruggen et al. (1998) also observed that an MMSS can reduce the difference between high- and low-analyticals. The paper by Brown in this issue provides some insights into this difference in cognitive style by showing how analytically trained advertising personnel use different decision rules to evaluate potential ads than those used by the creative staff.

The counterpart of the demand side is the *supply* side, i.e., the type of the decision support offered by the MMSS (Figure 1, Box 2). An MMSS can support a decision maker in different ways. It can help the manager carry out the actual calculations (e.g., find the "optimal" value), it can support the analysis and diagnosis of a specific situation, or it can come up with suggestions for users that stimulate the generation of (new) solutions. Perhaps most importantly, it can help frame the important issues and uncertainties associated with the problem at hand and in the process help the decision maker come to an acceptable decision. It is this feature of getting managers to think about the problem

Figure 1 **Integrative Framework of the Factors that Determine the Success of a Marketing Management Support System**



in a structured way and "quantifying" their beliefs that is often pointed to as the major benefit of MMSS. However, it is still important to determine if this structure leads to better firm performance.

MMSS can be classified as either being *data-driven* or *knowledge-driven.* Interestingly, only one paper in this issue, the paper by Goldenberg et al., is a prototypical example of a knowledge-driven system. In fact, no other paper submitted for review for this special issue fits into this classification. All of the other MMSS papers use existing databases, often coming from scanner data. Apparently, the developments in MMSS, so far, have been dominated by researchers with a model-building background who prefer data-driven approaches and who are attracted to available data. With this said, we note the diffusion of the achievements in cognitive science and artificial intelligence into the field of consumer decision making (e.g., Bettman 1979; Alba and Hutchinson 1987). We forecast that these advances will soon find their way into the study of managerial decision making and marketing decision support systems.

The success of MMSS depends on the match between demand and supply of the decision support (Figure 1, Box 3). Although such a match should be "obvious", it is useful to classify the types of problem-solving models found in MMSS and the conditions that favor the use of each type of mode.

Table 2 lists a possible partitioning of marketing problem-solving modes in four categories: optimizing, reasoning, analogizing, and creating, along with the main characteristics favoring each mode (Wierenga

Table 1 Demand Characteristics for Papers in this Issue

		Problem Structure: High	Problem Structure: Low
Environment	Stable	7, 10, 11, 12	3, 6
	Dynamic	1, 2, 8, 9	

Legend for Papers

Number	Title	Author(s)
1	Modeling the Evolution of Markets with Indirect Network Externalities: An Application to Digital Television	Gupta, Jain, and Sawhney
2	Risk Behavior in Response to Quotas and Contests	Gaba and Kalra
3	"Do the Right Thing:" Diverging Effects of Accountability in a Managerial Context	Brown
4	Industrial Pricing: Theory and Managerial Practice	Noble and Gruca
5	Commercial Use of UPC Scanner Data: Industry and Academic Perspectives	Bucklin and Gupta
6	The Fundamental Templates of Quality Ads	Goldenberg, Mazursky, and Solomon
7	SilverScreener: A Modeling Approach to Movie Screens Management	Swami, Eliashberg, and Weinberg
8	Development and Implementation of a Segment Selection Procedure for Industrial Product Markets	Montoya-Weiss and Calantone
9	The Dynamic Effect of Discounting on Sales: Empirical Analysis and Normative Pricing Implications	Kopalle, Mela, and Marsh
10	Accounting Profits vs. Marketing Profits: A Relevant Metric for Category Management	Chen, Hess, Wilcox, and Zhang
11	A Decision Support System for Planning Manufacturers' Sales Promotion Calendars	Silva-Risso, Bucklin, and Morrison
12	PromoCast™: A New Forecasting Method for Promotion Planning	Cooper, Baron, Levy, Swisher, and Gogos

Table 2 Analysis of Papers in this Issue by Functionality

Function of MMSS	Conditions Favoring Good Match	Papers*
Optimizing	analytic decision maker, highly-structured problem, stable market, ample time for decision	7, 9, 10, 11, 12
Reasoning	less-structured problem, changing markets, constrained time for decision	1, 8
Analogizing	nonanalytical decision maker, ill-structured problem, severe time pressure	3
Creating	no precise problem definition, no time pressure, divergent thinking, expanding the solution space	6

See Table 1 for legend of papers.

and Van Bruggen 1997). This table also gives our classification of the papers that fall into each category. We leave it up to the reader to determine if there is a good match between the model and the conditions being modeled.

The match between demand and supply of decision support determines the *potential* success of an MMSS. However, whether or not this potential will materialize depends on two sets of factors: *design* characteristics (Figure 1, Box 4) and *implementation* characteristics (Figure 1, Box 5). The effects of design characteristics and characteristics of the implementation process on the success of a system have been studied extensively in the *general* DSS/IS field. There is a large literature on these topics, summarized in several review papers and meta-analyses, such those by as Zmud (1979), Kwon and Zmud (1987), DeLone and McLean (1992), Alavi and Joachimsthaler (1992), and Gelderman (1997). Papers that have studied the effects of design and implementation process characteristics for MMSS (e.g., Zinkhan et al. 1987; Wierenga and Oude Ophuis

1997) tended to find similar effects as those in the general DSS/IS field. The most important design and implementation variables that have emerged from this work can be found in Figure 1, Boxes 4 and 5.

As we have seen earlier there are different ways to measure the *success* of an MMSS. From the start of research in the field of DSS/IS, the question of what the dependent variable should be has occupied an important place in the literature (Zmud 1979; Keen 1980; Ives and Olson 1984; DeLone and McLean 1992). So far, this has not led to the adoption of *one* IS success measure. DeLone and McLean (1992), who examined dependent variables in 100 empirical DSS/IS studies, concluded that "there are nearly as many measures as there are studies" (p. 61). We distinguish four levels of success for MMSS (Figure 1, Box 6): (a) *technical validity* (the extent to which the MMSS is a valid representation of the marketing processes and makes statistically accurate predictions); (b) *adoption and use of the MMSS;* (c) *impact for the user;* and (d) *impact for the organization.* We make a distinction between user impact and organizational impact. User impact variables refer to how well the MMSS performs in the perception of the user. User satisfaction is by far the most frequently used dependent variable in DSS/IS research (Gelderman 1997). The organizational impact variables such as profit, sales, and market share have a more objective character. Although an MMSS should ultimately be judged on the additional profits it generates, it is often easier to measure user perceptions or technical validity than the more qualitative (and valid) effects on organizational impact. This is reflected in the measures of success used for the papers in this issue (see Table 3). This table points out how difficult it is to get corporate buy-in to implement and test an MMSS against a control.

The above integrative framework summarizes the current state of knowledge with respect to the factors that drive the success of MMSS. In the next section we use this framework to discuss what we perceive to be the most important issues for further research in MMSS and to review the papers found in this Special Issue.

Table 3 Classification of Papers by Measures of Success

Technically Valid	1, 6, 7, 9, 10, 12
Adoption of MMSS	8, 11
Impact for User	– –
Impact for Organization	8, 11

See Table 1 the for legend of papers.

Research Issues for Marketing Management Support Systems

Designers and users of MMSS need to be aware of all the factors shown in Figure 1 because they all can affect ultimate success of a specific decision aid. As noted earlier, many of the design and implementation issues noted in Boxes 4 and 5 of Figure 1 are not specific to marketing and have been discussed in numerous literatures, especially those related to the DSS/IS field. Still, marketing decision situations have many unique characteristics associated with the marketing problems being studied, the decision makers interacting with the MMSS, and the environments in which decisions are being made. Below are some observations that can be made with respect to what has been achieved so far with MMSS and what we perceive are the most pressing future research issues.

Need for Studies in Real-Life Company Environments

We noted earlier that the number of studies on the effectiveness of MMSS that have used real-life marketing management situations is scarce. Laboratory studies can generate important knowledge about variables that affect the success of MMSS and the decision process used by managers. However, the results of these lab studies often lack external validity. We would like to see more studies that use controlled experimentation within a real-world field setting. Interestingly, none of the papers in this issue used such a procedure to measure the impact of the discussed decision aid. The paper by Goldenberg et al. used experimentation to verify the veracity of their advertisement-generating MMSS, but they did not test it within an advertising agency. The paper by Gupta et al. makes a number of predictions on the adoption of digital tv, but most of these predictions cannot be tested yet, because they are in terms of forecasts of future events. Montoya-Weiss and Calantone discuss in detail the implementation of their MMSS but they were not able to do any experimentation because there was no logical control (i.e., the firm either could implement the new strategy or not). Similarly, the paper by Silva-Risso et al. reported the results after their model was implemented by the client, but like the Montoya-Weiss and Calantone situation, could not use a control to determine changes in profitability.

This raises two major issues. First, what are the best ways to document improvements if there are no logical controls, e.g., the firm either fully implements the proposed strategy or does not? How can the researcher best predict what would have happened if the decision aid was not used? Second, what can be done to facilitate the use of more decision aids? Clearly, institutions such as the Marketing Science Institute and the Institute for the Study of Business Markets (ISBM) at Penn State provide help in this regard. Still, we believe that there needs to be more communication between the potential users of MMSS and the designers of these decision aids. Hopefully, the review papers in this issue by Noble and Gruca, who discuss current pricing practices, and Bucklin and Gupta, who discuss present uses of scanner data models, will help address this problem.

This leads to the next important issue: understanding more about how managers now go about making decisions.

Limited Knowledge of Managerial Decision Processes

Although the decision maker and his or her decision process constitute the core element of the demand side of MMSS, our knowledge of this element is still fairly limited. The marketing management literature abounds in recommendations of how marketing managers *should* make decisions. However, it is surprising that in a field that has extensively studied consumer decision making, we know so little about how marketing managers actually make decisions. We acknowledge that it is more difficult to "study" managers than consumers, but the payoffs from such studies could be great. Moreover, now that many academics are involved in executive education instruction, it may be more possible for them to use these participants as "subjects."

The list of possible topics for studying the managerial decision-making process is extensive. As reported earlier, much of the work to date has centered on cognitive style. Another relevant variable is experience (i.e., professional experience as a marketing decision maker). Recently, Spence and Brucks (1997) found that novices especially benefited from using a decision aid. In fact, these researchers questioned the usefulness of MMSS for experts. Experience has also been found to influence the use of information by marketing managers (Perkins and Rao 1990). A variant of this information use is seen in the paper by Brown in this issue. She reports that the weights placed on different attributes of the problem differed by discipline. These findings suggest that experience plays a possibly moderating role with respect to the success of MMSS. This is an interesting topic for further research.

Another recent line of research on managerial decision making is the work of Boulding et al. (1997, 1998). They initially studied managers involved in the launch of a new product offering and the subsequent decision of whether or not to terminate the launch. They noted that many managers tended to stick to a losing course of action (Boulding et al. 1997). They then proposed and tested the veracity of a number of decision aids that were designed to help managers overcome this bias (often referred to as an escalation bias). In a follow-up study (Boulding et al. 1998), these researchers found that managers exhibit a tendency to overweight their prior beliefs when they obtain and evaluate new information. Thus, if they start out with a positive belief about a project, they tend to see new (negative) information more positively than a neutral observer. Moreover, they weight their prior opinions more than predicted by a normative Bayesian updating model. All this leads to an overly optimistic viewpoint and thus the tendency not to disengage from a losing course of action. Studies of this type provide the MMSS designers with deeper insights into how managers decide how to decide. Such knowledge should help these designers construct new, more effective decision aids.

Finally, the paper by Gaba and Kalra in this issue presents a decision aid (in this case a compensation plan) that alters the way managers (salespeople) make choices among risky alternatives. As with the Boulding et al. papers, we note that the authors use a blend of behavioral theories and modeling to provide deeper insights into managerial behavior.

From Relatively Structured to More Complex Problems
There is a continuum of marketing problems for which MMSS can be developed, ranging from very structured problems in scientifically well-charted areas with substantial data, to ill-structured problems in scarcely explored areas where little is known. Many of the MMSS developed to date address relatively structured problems with easy to obtain data, such as sales planning, media planning, and shelf-space allocation (Simon 1994). This is illustrated by the five papers in this issue that use scanner data and address the issue of sales promotions of fast-moving consumer goods in supermarkets. However, it is encouraging to see that problems in other industries are also being addressed. This Special Issue contains one study by Swami et al. conducted in the movie industry, an industry with a very complex decision-making environment where managers tend to be very skeptical about analytical approaches. Other areas studied are the auto supply industry (Montoya-Weiss and Calantone), the digital tv industry (Gupta et al.), and the advertising industry (Goldenberg et al.). All these settings are very different from the well-known package goods scene. Moreover, managers in these industries tend to make their decisions using a mix of traditional decision rules or heuristics, intuition, experience, and hope. We encourage others to continue to develop MMSS that provide useful structure to help managers solve difficult and complex problems.

From Data-Driven to Knowledge-Based MMSS
Most MMSS developed so far have been of the mathematical modeling and optimization type, with a strong *data-driven* orientation. (See for example Table 3.) How can efforts be directed towards decision support for more complex or even ill-structured problems? One possibility is to cut the larger, complex problem into smaller "pieces" that can be structured and made amenable to quantitative analysis. After all, many problems of the world that are presented as ill-structured problems become well-structured in the hands of the problem solver (Simon 1973). This "divide-and-conquer" approach is seen in this issue in the studies of the digital tv industry (Swami et al.) and the automobile industry (Montoya-Weiss and Calantone), where smaller problems are isolated from larger problems and solved using an optimizing type of MMSS. Another way of addressing complex problems is by developing different types of decision aids. An important characteristic of ill-structured problems is that they are formulated in qualitative, rather than quantitative terms. In such a situation *knowledge-driven* MMSS can be used. These MMSS are based on knowledge representation and knowledge processing methods developed in the fields of artificial intelligence and cognitive science. A rich supply of expert systems, case-based reasoning systems, neural nets, and creativity support systems is emerging and can be applied in the marketing domain. For decisions in areas such as innovation, communication, and marketing strategy, case-based reasoning systems (making use of analogies) and creativity support systems can be very useful. These MMSS typically do not provide recommendations for the "best decision." Instead, as shown in this issue in the paper by Goldenberg et al. these knowledge-driven aids weed out poor decisions, make suggestions, and stimulate the thinking processes of the decision maker.

The effects of knowledge-based MMSS have not yet been systematically studied. Since the kind of decision processes that are supported by these systems (e.g., being creative, searching for analogous situations) appear quite frequently in the daily activities of marketers, we believe more research on the potential of knowledge-based systems in marketing is needed.

Emphasis on the Match Between Managerial Judgment and MMSS
Rarely is the decision left completely to the MMSS. Likewise, even though managerial judgment has its strengths, it also has its limitations, especially in environments characterized by unpredictable demand and rapidly changing consumer tastes. It has been demonstrated that the *combination* of human judgment and MMSS is a very powerful partnership (Blattberg and Hoch 1990; Gupta 1994). More insight is needed in how to accomplish the match that gets the most out of this combination of modeling and managerial judgment. Certain factors are known to increase this match.

Clearly, the supply side model characteristics should match the demand side needs. This issue of a good match gets attention in the studies by Noble and Gruca and Bucklin and Gupta. Both papers review current practices within the specific context being studies, and then lay out frameworks for thinking about the problem. Also, the paper by Montoya-Weiss and Calantone provides insights of how and why managers augmented the MMSS results to come up with solutions that blended their own judgment with the recommendations of the model.

As designers of MMSS become more involved in complex, unstructured problems, they will need to obtain more information on how managers now go about making these complex strategic decisions. The work of Boulding et al. (1997; 1998) is one such effort. Other examples are the work of Moore (1992), Moore and Urbany (1994), and Glazer et al. (1992). We encourage others to study the managerial decision-making process and to provide new insights as to how to blend managerial knowledge with decision aid output to arrive at better decisions.

Should MMSS Reinforce or Compensate?

The requirement of a good fit between the decision maker and the MMSS raises the issue of reinforcement or compensation. Should the decision maker be provided with a system that reinforces his strengths, or should the system compensate for his weaknesses? In the first case analytically oriented decision makers would be provided with sophisticated marketing models. Another strategy would be to provide less analytic (i.e., more heuristically oriented) decision makers with marketing models. Although the latter group probably has more to gain from such a system, getting such people to work with systems that do not fit with their cognitive style requires more effort, and may not even be feasible. A trade-off needs to be made, and the question of whether it is more effective to give an MMSS a reinforcing or a compensatory role needs attention in future research. Here we point to the paper by Brown, which provides some insights into the different cognitive styles of decision makers.

From Technical Validation to Organizational Validation

As can be seen in Box 6 of Figure 1, there are several potential measures of success for MMSS. Technical validity is an a priori condition for the positive impact of an MMSS on company results. However, it is still far removed from the ultimate measure of success, i.e., positive impact on company results. We already discussed the need to move MMSS from the academic arena into the corporate world. Only then will it be possible to determine the impact on organizational performance. Also, based on prior results (Van Bruggen et al. 1996, McIntyre 1982, Chervany and Dickson 1974, Schewe 1976) that show a very weak correlation between self-assessment measures, e.g., satisfaction and perceived accuracy, and objective measures of performance, we suggest moving away from self-assessment measures as proxies for better performance. The lack of relationship between objective and subjective variables also leads us to believe that this may be a barrier to the increased adoption and use of MMSS because decision makers do not seem to be able to independently judge the (positive) impact of an MMSS on firm performance. It also calls to attention the need to establish some baseline of performance that would have occurred if the MMSS was not implemented. In this regard, the papers by Silva-Risso et al. and Kopalle et al. provide some useful methodology for establishing baselines for sales before promotions. The three papers by Swami et al., Montoya-Weiss and Calantone, and Cooper et al. lay out procedures for establishing baseline for their particular situations. Still, it might be interesting if the firm were to use an independent third party to formulate and determine a metric for performance of MMDS prior to its implementation. Then, suppliers of ready-to-use MMSS could provide performance measures relative to these predetermined standards.

Time Pressure, Dynamics, and Integrated Systems

There are three additional items not explicitly dealt with in the papers in this Special Issue that we feel should receive attention in the work on MMSS. *Time constraints* often preclude the execution of elaborate solution procedures. Time pressure has been recognized as an important variable in information systems design, but empirical studies on this variable have been sparse (Hwang 1994). Time pressure causes selective and reduced information search and superficial processing (Hogarth and Makridakis 1981). Furthermore, time pressure leads to a tendency of "locking in on a strategy" (Edland and Svenson 1993), and to simplifying strategies and conservative behavior (Hwang 1994). Van Bruggen et al. (1998) reported that decision makers benefited most from an MMSS under low time pressure conditions. On the one hand an MMSS can help decision makers to refrain from suboptimal behavior; on the other hand, use of an MMSS also costs time. Further research should give a better insight regarding the trade-off between these two factors.

When considering the match between the demand and supply side of marketing management support one should be aware of the *dynamics* of the situation. The availability and use of MMSS may very well change the demand side of support. For example, a particular decision aid may increase the knowledge about a problem and make the problem situation more structured. This changes the characteristics of the decision situation and may make it possible to apply optimization where this was not possible before. It has been documented that the availability and use of decision aids affects the way decision makers solve problems (Benbasat and Todd 1996). Organizations may also learn from the use of MMSS. Changes in the characteristics of the decision situation may lead to a different marketing problem solving mode, which in turn may require a different MMSS. These dynamics in the demand for MMSS is an interesting research topic. Companies may go through successive generations of MMSS, where for each subsequent MMSS the requirements differ from its predecessor.

Finally, nowadays there is a tendency towards companywide information systems, with *integrated* modules for the different functional areas, such as production, logistics, marketing, and finance (so-called Enterprise Resource Planning (ERP) systems). In this issue, the paper by Chen et al. provides a mechanism for retailers to cut across the sales data of the different department to determine total store profits associated with attracting a shopper with one particular category advertisement. In addition, Montoya-Weiss and Calantone model the interdependence of marketing and R&D, and Swami et al. model the relationship between marketing strategy and technology strategy. These three papers are good examples of MMSS that provide support for several areas of management. Integration of marketing support systems in broader management support systems makes MMSS accessible to a wider range of decision makers, including nonmarketing managers. It also calls for additional research to clarify any additional requirements for MMSS that are implied by this extended demand side.

Summary

We have discussed the most important developments and research issues with respect to the success of MMSS. We hope that this discussion, together with the integrated framework presented earlier, provides the reader with a clear picture of the state of the art in this area and provides a useful perspective for studying the other papers on marketing decision making and marketing decision support in this Special Issue. We hope this Special Issue will also stimulate and direct further research in this important area of marketing science.

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