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Marketing Decision Making and Decision Support: Challenges and Perspectives for Successful Marketing Management Support Systems

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Abstract

Marketing management support systems (MMSS) are computer-enabled devices that help marketers to make better decisions. Marketing processes can be quite complex, involving large numbers of variables and mostly outcomes are the results of the actions of many different stakeholders (e.g., the company itself, its customers, its competitors). Moreover, a large number of interdependencies exist between the relevant variables and the outcomes of marketing actions are subject to major uncertainties. Given the complexities of the market place, marketing management support systems are useful tools to help the marketing decision makers carry out their jobs. Marketing management support systems can only be effective when they are optimally geared toward their users. We, therefore, deal with decision making in marketing (which generates the need for marketing management

support systems). We discuss how marketing decisions are made, how they should be made, and the relative roles of analytical versus intuitive cognitive processes in marketing decision making. We also discuss the match between marketing problem-solving modes and the various types of marketing management support systems. Finally we discuss how the impact of MMSS can be improved. This is important, given the current under-utilization of MMSS in practice. We discuss the conditions for the successful implementation and effective use of marketing management support systems. The issue ends with a discussion of the opportunities and challenges for marketing management support systems as we foresee them.

1

Marketing Processes, Marketing Decision Makers, and Marketing Management Support Systems: Introduction to the Issue

This issue of Foundations and Trends in Marketing addresses the topic of marketing management support systems. In brief, marketing management support systems (MMSS) are computer-enabled devices that help marketers to make better decisions (a more elaborate definition follows later). As shown in Figure 1.1, marketing decision making involves three important entities: marketing processes, the marketing decision maker, and the marketing management support system. Marketing processes (left box of Figure 1.1) comprise the behavior and actions of customers, resellers, competitors, and other relevant parties in the marketplace. Marketing decision making implies interfering in these marketing processes with the purpose of influencing them in a way that serves the objectives of the company. In principle, marketers use the instruments of the marketing mix for this purpose; they offer products, carry out advertising and other promotional activities, they set prices and choose distribution channels through which the products are marketed. Marketing processes can be quite complex, involving large numbers of variables and mostly their outcomes are the results of the actions of many different stakeholders (e.g., the company itself, its customers, its competitors). Moreover, usually, a large number of

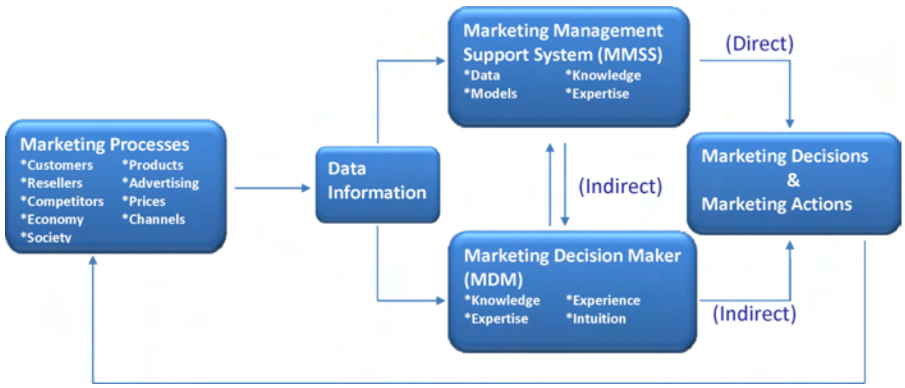

Fig. 1.1 Marketing processes, the marketing decision marker, and the marketing management support system.

interdependencies exist between the relevant variables and the outcomes of marketing actions are subject to major uncertainties. Finally, to make things even more complicated, marketing processes do not take place in isolation, but within the broader context of the economy and the society at large. Given these complexities of the marketplace, marketing management support systems are needed to help the marketing decision makers carry out their jobs.

The marketing decision maker (represented by the central box in Figure 1.1) receives a constant stream of data about marketing processes with respect to the products and brands she/he is responsible for. Marketers use these signals to monitor what is going on, they try to interpret this information to understand the underlying mechanisms of the observed phenomena in the market, and use the resulting insights to take appropriate actions. Usually, marketing decision makers bring an impressive set of assets to the table. They possess knowledge about marketing phenomena, experience with marketing processes in practice, specific knowledge (e.g., industry-specific expertise), and a good deal of intuition. All these elements can be deployed to convert the information about marketing processes into effective decisions. However, at the same time, marketing decision makers are also constrained by serious limitations. Perhaps the most severe limitation is time. It is well-known that managerial activity is characterized by brevity, variety, and discontinuity (Mintzberg, 1973), and marketing management is no exception. In their day-to-day decision making marketing managers have to allocate their time over a large number of different problems, which makes it extremely difficult to pay concentrated attention to each individual problem. Another limitation is cognitive capacity. As a human being, a marketing decision maker is able to process only a limited amount of information and to consider only a limited number of alternative solutions for a problem at the same time (Miller, 1956). Again, being humans, marketing decision makers are subject to biases, may suffer from overconfidence, and get tired, bored and emotional (Hoch, 2001). Usually it is not sufficient for marketing decision makers to just look at the data and "Let the data speak" is often a too simplistic advice. Analysis is needed to develop insight into the causes of the observed events. For example, why do we see a sudden drop in market share in country X?; why is the performance of this new product so far below the prognosis? To answer such questions, marketers need help from sophisticated decision aids.

This takes us to the core topic of this issue: the marketing management support system, as shown upper-center in Figure 1.1. Marketing management support systems (MMSS) enhance the decision making capabilities of marketers, by improving their efficiency (saved time) as well as their effectiveness (better decisions). As shown in Figure 1.1, a marketing management support system is fed with data about the processes in the marketplace, is in constant interaction with the marketing decision maker, and its output has impact on marketing decisions and marketing actions. The influence of an MMSS[1] on marketing decisions can be either *direct*, that is when specific decisions are completely left to the MMSS (=marketing automation) or *indirect*, that is when marketers take the output of the MMSS into account when making their decisions. As we will see later, at this point in time the indirect way is by far prevalent. Marketing automation is only possible in very specific situations. Marketing decisions and actions, incorporating the influence

[1] Throughout this issue we use the acronym MMSS for the singular (marketing management support system), as well as for the plural (marketing management support systems).

of the MMSS, in turn affect the processes in the marketplace. This is shown by the feedback loop in Figure 1.1.

A marketing management support system can perform different roles. An MMSS can primarily act as a data repository, which is a device that monitors events and provides information about these events to decision makers in such a way that they can easily use it. In this role the MMSS answers the "*what* happened?" question. A more sophisticated MMSS can help detecting cause–effect relationships between events in the marketplace. The MMSS answers the "*why* did it happen?". For example, did we sell so much more because our sales-promotion campaign was extremely effective, or because the competitor reduced the size of its sales force? Next, an even more sophisticated MMSS can consider alternative marketing actions and predict the (conditional) outcomes of these actions. Such an MMSS is able to answer "*what-if?*" questions. For example, what happens to our sales and profit if we would increase the advertising budget with x%? Finally, an MMSS reaches the highest level of sophistication and functionality when it answers the "*what should* happen?" question. "Should we introduce this new product or should we increase our advertising budget with 50% in order to realize our profit target?" are examples of such questions.

MMSS in practice almost always contain a database and the functionality to retrieve data from it. Data are needed for answering the "what" question. In addition an MMSS can contain models which are needed for the analysis of cause-and-effect relationships, for simulations, and for optimization. These are the higher functionality levels of an MMSS. A marketing management support system is not limited to containing quantitative data only. It can also contain qualitative data in the form of knowledge and expertise, for example, in the form of if-then rules in marketing expert systems. The interaction between the marketing decision maker and the MMSS can take different forms. In a very basic form the MMSS sends periodic information to the decision maker, for example, figures about sales, market shares, and profits per month, per week, or even per day. Often, the user can drill down in this data, for example, to look at specific customers groups, specific channels, or specific geographical areas. In an interactive way, the marketing decision maker can also ask specific questions to the MMSS, about facts (what) or about the relationship between marketing instruments and sales (why). Furthermore, as described above, the marketer can also ask the system to carry out simulations (what-if) or to provide recommendations (what should). Examples of the latter are recommendations for the optimal advertising budget in a fast-moving consumer good company (Little, 1970) or for the best movie schedule in a movie theatre (Eliashberg et al., 2009a).

Relative to other management areas such as finance and operations management, marketing is a domain where human experience and expertise have always played an important role. Many marketing processes are weakly structured and require a good deal of human judgment. Although in this issue we do discuss marketing decisions that can be automated (e.g., in the domain of CRM), many marketing decisions calls for a combination of the judgment, intuition, and expertise of the manager and the analytical capabilities of the MMSS. The best performance in the marketplace will be obtained when the strengths of both models *and* intuition are used (Hoch, 2001). In Section 5 we discuss in more detail how the *combination* of the marketing decision maker and MMSS improves the performance of marketing decision makers.

1.1 The History of Marketing Management Support Systems

The idea of designing systems and models to assist marketers' decision making dates back to over forty years. In (1966), Kotler introduced the concept of a "Marketing Nerve Centre," providing marketing managers with "computer programs which will enhance their power to make decisions." The first of these systems were *marketing information systems* (Brien and Stafford, 1968). The computers that were introduced at that time in companies produced lots of data and a systematic approach was needed to make those data available in a way such that managers could effectively use them for decision making. There was a serious danger of overabundance of irrelevant information (Ackoff, 1967). About ten years later, Little (1979b) introduced the concept of *marketing decision support systems.* He defined a marketing decision support system (MDSS) as a "coordinated collection of data, systems, tools and techniques with supporting software and hardware by which an organization gathers and interprets relevant information from business and environment and turns it into an environment for marketing action" (p. 11). Little's (1979b) concept of an MDSS goes much further than a marketing information system. Important elements are models, statistics, and optimization, and the emphasis is on response analysis; for example, how sales respond to promotions. In Little's view, MDSS were suitable for structured and semi-structured marketing problems, had a quantitative orientation and were data-driven.

Almost two decades later, Wierenga and Van Bruggen (1997) presented a classification of marketing decision support technologies and tools, and used the term "Marketing Management Support Systems" to refer to the complete set of marketing decision aids. In addition to the *data-driven* marketing management support systems as defined by Little (1979b), marketing management support systems also include *knowledge-driven* systems aimed at supporting marketing decision making in weakly structured areas. Data-driven MMSS use quantitative data analysis techniques and econometric and operations research models. Knowledge-driven MMSS systems use technologies from Artificial Intelligence (AI) such as expert systems, analogical reasoning, and case-based reasoning and have been developed more recently (Wierenga et al., 2008). We provide an overview of the different marketing management support systems in Section 2.

Since the introduction of the first generation of marketing management support systems the conditions for using these systems in companies have greatly improved. The main reason for this is the enormous progress in information technology. Today, almost every marketing decision maker works in an IT-supported environment and is directly and continuously connected to databases with information about customers, sales, market shares, distribution channels, and competitors. Many companies interact directly and continuously with customers and prospective customers through multiple channels like the internet, mobile devices, call centers, and physical stores. All of these interactions generate customer data. The stored customer data concern very detailed information about all phases of customers' purchasing processes from individuals' information search and transactions activities to post-purchase information and service requests. Increasingly, data are collected at a very disaggregate level. This means that it is possible to collect data for each individual customer for every activity this person undertakes at each point in time. Similarly, information technology has made it possible in many markets to continuously track the behavior and the marketing activities of competitors. Increased computer storage capacities allow for the storage of all of these data and increased processing capacities make it possible to analyze these data (in real-time). Decision support models, increasingly, run real-time and provide instant support about which marketing activity to undertake for a particular customer in a specific situation (Reinartz and Venkatesan, 2008).

When we look at the use of MMSS in practice, we observe that the information retrieval function of MMSS, related to the "what" question mentioned earlier, is used quite extensively. However, this is much less the case for other, more advanced and sophisticated functionalities of MMSS. As a consequence, the impact of marketing management support systems in practice is lower than its potential. About ten years ago, Bucklin et al. (1998) presented an optimistic view on the impact of decision support systems in marketing. They argued that a growing proportion of marketing decisions could not only be supported but might also be automated. They foresaw that close to full automation would ultimately take place for many decisions about existing products in stable markets. However, even in established markets such as for consumer-packaged goods, marketing automation has not taken off yet. Interestingly, in quite different industries, those where the Customer Relationship Management (CRM) approach has taken hold (e.g., financial services, telecommunication, (former) catalogue companies), we now do see the realization of marketing automation. In companies in these industries computers decide, for example, which customers will receive a specific offer and which customer will not. However, MMSS offer many more possibilities and there must be reasons why companies do not use MMSS to their full capacity yet. It is important to identify potential barriers so that these can be removed.

1.2 Content of This Issue

In this issue of Foundations and Trends in Marketing we focus on the center part of Figure 1.1. The main subject is marketing management support systems. Since these systems can only be effective when they are optimally geared toward their users, we also address the users of these systems, the marketing decision makers, as well as the interaction between MMSS and their users.

Section 2 deals with the *demand side* and deals with decision making in marketing (which generates the need for decision support system). We discuss how marketing decisions are made, how they should be made, and the relative roles of analytical versus intuitive cognitive processes in marketing decision making. Section 3 discusses the ORAC classification of marketing problem-solving modes. The next section (Section 4) discusses marketing management support systems in detail. What different types of MMSS exist and how have they developed over time? Marketing management support systems constitute the *supply side* of marketing decision support. In Section 4 we also discuss the match between marketing problem-solving modes and the various types of marketing management support systems. In Section 5 we discuss how MMSS support marketing decision makers and reflect on the best way of combining the strengths of the human decision maker with the strengths of the computer. We also address the impact of MMSS; what are the documented effects of MMSS on decision making? Section 6 discusses how can we improve the impact of MMSS. This is important, given the current under-utilization of MMSS mentioned before. We discuss the conditions for the successful implementation and effective use of marketing management support systems in practice. This issue ends with a discussion of the opportunities and challenges for marketing management support systems as we foresee them.

2

Decision Making in Marketing

Marketing decision making concerns decisions about marketing instruments that affect marketing processes (see Figure 1.1). These decisions refer to a broad range of topics such as how to market, which products, in which markets, through which channels, at which moments in time for what prices, and supported by which marketing communication activities. Decisions will differ in importance, impact, and frequency with which they are taken. The way decisions are made, or the decision process, will also differ in different decision situations. The characteristics of decisions and of decision processes determine the requirements for decision support and the extent to which a specific type of marketing management support system can be expected to be effective. In this section we discuss different approaches to marketing decision making.

2.1 Descriptive Approaches to Marketing Decision Making

Whereas the field of marketing started out as an economic discipline, around the 1960s the behavioral sciences became more prominent. Two influential books at that time, "Marketing Behavior and Executive Action" (Alderson, 1957) and "Marketing: Executive and Buyer

Behavior" (Howard, 1963), explicitly discussed how marketing executives and buyers actually make decisions in practice. Putting the spotlight on how human decision makers concretely behave in companies and households was very different from the prevailing economic approach which treated concepts such as firms, consumers, and markets in a very abstract way. Both in the Alderson book and in the book by Howard, the behavioral approach focused on two entities: the buyer (or consumer) and the marketing executive. Since the 1960s, research in consumer decision making has resulted in a large literature and a rich body-of-knowledge. For the other entity, decision making of marketing executives, the follow-up in terms of behavioral research has been much less spectacular. It started with an interest in topics such as decision centers (where are marketing decisions being made?), decision authority, organizational structure (e.g., what is the best structure of a sales organization), and in marketing budget decisions. From there, researchers began to document how marketing decisions makers in companies actually make decisions. For example, researchers developed flow charts for typical decisions (e.g., pricing decisions) describing how a decision maker would act given particular actions from the competitor. Such flow charts were called "pricing programs" (Howard, 1963). An example of a pricing program is the following: *An executive will monitor his largest competitor's price. If (s)he observes a change in this competitor's price in a particular area, (s)he looks at his own market share. If his market share is smaller than the share of his competitor, and the competitor's price had decreased (s)he will follow this decrease.* In the case of an increase of the competitive price, the reaction is more difficult, because an increase carries the danger of losing market share to another competitor. If the market share of the focal company is greater than that of the largest competitor, another portion of the competitive pricing program is executed (Howard, 1963, pp. 15–18). This "decision process approach" describing the decision process of marketers using interviews and protocol analysis became quite popular. Most of the studies were on price decisions (list price decisions and price adjustment decisions), but also a good deal of effort was put in finding out how companies make advertising decisions (especially about the advertising budget), how they make decisions about new products, and how they make forecasts (especially sales forecasts) (Hulbert, 1981). General findings in these studies are: (i) decision makers mainly use the past as their reference (incremental behavior); (ii) decision rules are very simple; (iii) no such concepts such as sales response functions (how sales respond if we increase advertising with x%?) are used; and (iv) marketing decisions are very much a part of the wider organizational decision process. It should be observed that the marketing decisions that were the object of decision process research were practically all repetitive decisions of a "programmed" nature. The "unprogrammed" type of decisions, found mostly at the highest organizational levels, was omitted, because "not enough is known" (Howard, 1963, p. 39).

Descriptive studies of marketing decision processes are useful, because understanding of current decision making can help improve the quality of future marketing decision making. For example, through the development and use of normative models or other marketing management support systems. However, the methodology of this type of studies is complicated. It is not easy to observe managerial decision making in an unobtrusive way, and often interviews are needed with large numbers of individuals, especially in the situation of more strategic, higher-level decisions where many persons are involved. Also, it is difficult to generalize from in-depth studies of only a small number of decision makers in only a small number of companies, how thoroughly they have been carried out. For example, the "pricing program", referred to earlier, was based on studying the price decisions of just one executive (Howard and Morgenroth, 1968). Later, descriptive studies of marketing decision processes became less popular. An example of a more recent date is a study of how product managers use scanner data (Goldstein, 2001). On the basis of in-depth interviews with six product managers of a large grocery manufacturer and other collected materials, Goldstein concluded that for the interpretation of scanner data pattern recognition plays an important role and that managers organize their understanding of the market environment as stories. They have a number of standard stories available (e.g., of how a sales promotion works), which they modify in light of the findings of the actual case. Another recent example of a descriptive marketing decision study examines how marketers reason about competitive reactions (Montgomery et al., 2005). Their methodology was to interview managers about past behavior and also to ask participants of the MARKSTRAT marketing game about their decision making during this game. The most interesting finding was the low incidence of strategic competitor reasoning (for example compared to reasoning about the customer). The use of the MARKSTRAT game as a realistic environment for observing "actual" marketing decision making has been practiced by several other researchers (Gatignon, 1987). These descriptive studies, although limited in number, provide useful insights in how marketing decisions are made.

2.2 Normative Approaches to Marketing Decision Making

The previous section was about how marketing decision makers *do* behave. Here we discuss how marketing decision makers *should* behave, That is, what is the best course of action in a given situation? In order to deal with this question there are two important issues. First, we need to be able to judge how good a particular decision is, that is we need an objective against which the result of a marketing action can be evaluated. In many situations the objective is to maximize profit, but there can also be situations where maximizing market share or maximizing sales is the first priority. Second, we need to know how different possible actions influence the processes in the marketplace and, ultimately, the objective(s) of the marketer. For example, a marketer may consider different levels of the advertising budget. In that situation, (s)he wants to know, for each level of the budget considered, how much additional sales it will generate, that is how sales respond to advertising. The gross margin on these additional sales minus the advertising expenditures is the contribution to profit of a particular advertising effort. So the key element here is the relationship between marketing efforts (in this case advertising expenditure) and sales. Such a relationship is called a sales response function. Once response functions are known, making a marketing decision can, in principle, be considered as solving an optimization problem. The theoretical conditions for the optimum values of the marketing variables, including the ratios between the different marketing mix instruments, are provided by the famous Dorfman and Steiner (1954) conditions.

2.2.1 Optimization

With the introduction of mathematical optimization tools, offered by the field of Operations Research, it became possible to carry out optimization of the marketing instruments in practical marketing situations. As we have seen earlier, in marketing the use of Operations Research (also called Management Science) became popular in the 1960s and this constituted the definite breakthrough of a quantitative-analytical approach to marketing problems. Kotler's (1971) textbook "Marketing Decision Making: a Model Building Approach" is an excellent exposition of this development. This comprehensive book starts out with formulating the marketing decision problem as a (mathematical) marketing programming problem (pp. 16–17). The objective is to determine the values of the marketing decision variables (the marketing mix instruments) that maximize the objective function, given the state of the environment (including competition) and taking into account relevant constraints such as the size of the market budget. If the sales response functions for the marketing decision variables are known, this mathematical programming problem can, in principle, be solved. In the 1960s the use of OR sometimes took the form of a technique seeking for a task. The most conspicuous example of this is the application of linear programming to media planning (Engel and Warshaw, 1964). Media-planning problems are not really linear, but were forced to be so, in order to solve them with linear programming. Later, marketing problems as such became the point of departure, and researchers started to realize that OR algorithms can be too much of a straightjacket for real-world marketing problems. Marketing models then became an important field in itself, relatively independent from Operations Research (Wierenga, 2008b).

2.2.2 Marketing Decision Making under Uncertainty

Most marketing decisions involve uncertainty. For example, we do not know how many customers will buy the new product that we consider to launch; we do not know whether or not our main competitor will follow a price cut that our company has initiated; and we do not know what the weather will be at an open air sales promotion manifestation that our company is considering to stage. A formal treatment of uncertainty is the expected utility theory of Von Neumann and Morgenstern (1947). This theory starts from a set of axioms about the outcomes of possible actions. Examples of such axioms are orderability (e.g., the decision maker is able to say what outcome (s)he likes most, what (s)he likes second best); transitivity (if a decision maker prefers A to B, and (s)he prefers B to C, then (s)he also prefers A to C); and continuity (if a decision maker has the transitive preference A > B > C, then there must be a lottery between A and C with probability p of A winning, that makes her/him indifferent between that lottery and B). On the basis of the complete set of axioms, it can be shown that a rational decision maker should choose that alternative from a set of available alternatives which maximizes his expected utility (Plous, 1993). In the 1950s and 1960s, the expected utility approach to decision making in business problems was very popular (Schlaifer, 1959). Expected utility theory forms the basis of decision analysis, an approach to the solution of practical problems (Howard, 1968). Decision analysis has also been applied to marketing problems, often in combination with a modeling approach. For example, in pricing decisions with uncertainty about the competitive response and in new product decisions with uncertainty about the profitability (Montgomery and Urban, 1969, Chapters 4 and 7). The expected utility approach implies that in the objective function profit is replaced by utility. Carrying out a decision analysis involves the estimation of (subjective) probabilities of elementary events, given specific courses of action, and determining the utility function of the decision maker for various outcomes. The shape of the utility function reflects the risk attitude of the decision maker, which is the extent of risk aversion, that is how risk averse he or she is (Pennings and Smidts, 2004).

Decision analysis again is a normative approach. Given the subjective probabilities and given the risk preference, there is a particular course of action that the decision maker *should* take. Theoretically, decision analysis is an attractive approach to marketing decision making. However, in practice it is very rarely used. One reason for this are the very demanding assumptions and requirements. For a particular decision, a marketer should be able to list not only all possible outcomes under all possible actions and states of nature, but also their probabilities. Furthermore, the actual encoding of the subjective probabilities and the estimation of the risk preference of a decision maker are far from trivial.

2.3 Non-Routine Decision Making: Satisficing versus Optimizing

The descriptive analysis of marketing decision making as well as the (normative) modeling approach to marketing decisions most often refer to decisions that occur frequently. Examples of such decisions are the response to a price change of the main competitor and determining the advertising budget. However, many marketing decisions are unique. They need to be made in a specific situation that will most likely not occur again. Moreover, often marketing problems are not very well-structured, or programmed. Examples of such problems are strategic decisions about acquiring a brand or a company, the design of a new product, and the choice of a long-term advertising theme. For such decisions, one would often also like to follow a rational decision process. According to Bazerman (1998) a rational decision making process consists of the following six steps:

(1) definition of the problem;
(2) identification of the criteria;
(3) weighting of the criteria;
(4) generation of alternatives;
(5) rating of each alternative on each criterion; and
(6) the computation of the optimal decision.

This rational model of decision making describes how an optimal decision making process *should* look like rather than what it *does* look like. Often, it will be impossible for decision makers to reach a high degree of rationality (Hogarth and Makridakis, 1981; Simon, 1997). The number of alternatives they must explore is so large and the information they would need to evaluate them so vast that even an approximation to objective rationality is hard to conceive. Introducing uncertainty and using the expected utility approach would make things even more complex. Actual behavior falls short of objective rationality, in at least three ways (Simon, 1997). First, rationality requires a complete knowledge and anticipation of the consequences that will follow on each choice. In reality knowledge of consequences will often be fragmented. Second, since consequences lie in the future, imagination must supply the lack of experienced feelings in attaching value to them. But values can be only imperfectly anticipated. Third, rationality requires a choice among all possible alternative behaviors. In actual behavior, only a very few of all these possible alternatives come to mind.

In 1955, Herbert Simon already wrote that because of bounded rationality, decision makers often will not maximize but satisfice. This means that they look for a course of action that is satisfactory enough. Decisions are made based on relatively simple rules of thumb that do not make impossible demands upon their thought capacity. In fact, most significant decisions are made using judgment rather than by a defined prescriptive approach (Bazerman, 1998). Managers make hundreds of decisions daily. Mintzberg (1973) reports that an average manager engages in a different activity every nine minutes. This will make a systematical and analytical approach difficult if not impossible. In making decisions, managers tend to avoid hard, systematic, analytical data and rely more on intuitive judgment.

Kahneman and Tversky (1974) suggest that people rely on a number of simplifying strategies, or rules of thumb, in making decisions. These strategies are called heuristics. They help in coping with the complexity that managers face. In this sense they are helpful. However, they can also lead to serious errors. Research of Hoch and Schkade (1996), for example, shows that although the intuitively appealing anchoring and adjustment heuristic may perform well in highly predictable environments, it performs poorly in less predictable environments. Simplification and relying on intuition may lead to error, but there is no realistic alternative in the face of the limits on human knowledge and reasoning (Simon, 1997).

Bazerman (1998) describes three general heuristics. The first one is the availability heuristic. Managers assess the frequency, probability, or likely causes of an event by the degree to which instances or occurrences of that event are readily "available" in memory. This heuristic can be useful since instances of events of greater frequency are generally revealed more easily in our minds than events of less frequency. Consequently, this heuristic will often lead to accurate judgment. The heuristic is fallible, however, because of the fact that the availability of information is also affected by other factors that are not related to the objective frequency of the judged event. Glazer et al. (1992) show, in the context of marketing decision making, that the use of this heuristic may lead to what they call "locally rational decision making." In an experimental study they found that decision makers especially use the information that is available or easily accessible. This leads to putting a lot of effort in making decisions on variables for which the information is available. Decisions on these variables will probably benefit from the use of the available information. However, it may well be that these specific variables are not the most important determinants of performance and that for superior performance it would be better to focus on other decision variables, even if information on these variables is difficult to obtain.

The second heuristics is the representativeness heuristic. Applying this heuristic means that managers assess the likeliness of an event's occurrence by the similarity of that occurrence to their stereotypes of similar occurrences. Managers, for example, predict the success of a new product based on the similarity of that product to past successful and unsuccessful product types. A problem is that individuals tend to rely on such strategies, even when this information is insufficient and better information exists.

A third general heuristic is the anchoring and adjustment heuristic. Managers make assessments by starting from an initial value and then adjust it to yield a final decision. The initial "anchor" may be suggested from historical precedent of random information. So a marketer might tend to set this year's advertising budget at a level close to last year's budget even though the market may demand something completely different this year (Van Bruggen et al., 1998). Adjustments from the initial value often tend to be insufficient and non-optimal since they are biased toward their initial values (Slovic and Lichtenstein, 1971) which may be insufficient for present market conditions (Mowen and Gaeth, 1992). Different initial values can yield different decisions for the same problem.

The problem with heuristic decision processes is that they can become so habitual or automatic that they will be applied even in situations where it would be preferable to use more formal or rational procedures and where the use of heuristics could lead to serious biases (Weber and Coskunoglu, 1990). Still Payne et al. (1993) characterize the use of simplifying, heuristic strategies that are selective in the use of information as *intelligent* responses, given that people have multiple goals for decisions. An individual's use of one of the multiple decision strategies in different situations is an adaptive response of a limited-capacity information processor to the demands of complex decision tasks. People make a tradeoff between the desire to be accurate (make a decision as good or rational as possible) and the desire to conserve limited cognitive responses (save cognitive efforts). The biases show that expertise will not automatically imply rational decision making processes. In fact, sometimes it might even be a cause of biased decision processes. However, experts possess the ability to respond intuitively and often very rapidly. This is the product of stored knowledge because of training and experience, which stimulates problem solving by recognition. Intuition, judgment, and creativity are basically expressions of capabilities for recognition and response based on experience and knowledge (Simon, 1997). According to Simon analytical (which can be interpreted as rational) and intuitive are no opposites. The power of analysis depends on expert knowledge for its speed and effectiveness. Among experts relative differences in their reliance on analysis as against intuition may be observed, but large components of both, closely intermingled, in virtually all expert behavior can be expected to be present. Therefore, it is doubtful that there are two types of managers, one of whom relies almost exclusively on recognition (intuition), the other on analytical techniques. More likely, there is a continuum of decision making styles involving a combination of the two kinds of skill. Simon concludes that it is a fallacy to contrast "analytic" and "intuitive" styles of management. Intuition and judgment — at least good judgment — are simply analyses frozen into habit and into the capacity for rapid response through recognition of familiar kinds of situations. A manager thus should not choose between the two styles but should have command of the whole range of management skills and applying them whenever they become appropriate.

Marketing Management Support Systems can support decision makers by augmenting and strengthening their analytical capabilities. These systems will be less restricted by computational and information storage resources than human marketers and can support these marketers in processing large amounts of information. This way, marketers can apply both their own judgmental and intuitive resources and the MMSS's analytical capacities to make decisions as good as possible. Marketing management support systems can compensate for the limited cognitive capacity of the marketing decision maker in two ways: (i) by decreasing the decision time (more efficient decision making); and (ii) by improving the quality of the decision (more effective decision making). Of the course a combination of the two is also possible.

2.4 Dual-Process Decision Making

Decision making can be based on intuition or analysis. This distinction has received a lot of attention over the last decades. Following works by authors such as Bruner, Epstein, and Hammond, there now is a consensus that there are two fundamentally different modes of how people think and reason, which are based on two different cognitive systems. Different authors have given different labels to the two systems. For example, Bruner (1986) speaks of "narrative" versus "paradigmatic" modes of functioning. Epstein (1994) defines the contrast as "experiential" versus "rational". Hammond (1996) uses the expressions "intuitive cognition" and "analytical cognition".

2.4.1 Two Systems of Decision Making

Recently, the two different cognitive systems have been labeled simply as *System 1* and *System 2* (Stanovich and West, 2000; Kahneman, 2003), see Table 2.1. System 1 is automatic, effortless, parallel, and not accessible for introspection, because it works unconsciously. System 1 is very fast: decisions are made in an instant, "in the *blink* of an eye"

Table 2.1. Two systems of decision making (Kahneman, 2003) and their relationship with marketing problem-solving modes.

System 1 (Intuition)	System 2 (Reasoning)
Fast	Slow
Parallel	Serial
Automatic	Controlled
Effortless	Effortful
Associative	Rule-governed
Slow-learning	Flexible
Emotional	Neutral
Marketing problem-solving modes	Marketing problem-solving modes
Analogizing	Optimizing
Creating	Reasoning

(Gladwell, 2005). System 2 is slow, controlled, effortful, serial, and conscious. Under System 2, a person thinks about a problem in terms of concepts, relationships between concepts, principles, and applies *rules* to arrive at a decision. Therefore, System 2 is also called rule-based (Stanovich and West, 2000). In Table 2.1 we profile the two systems. In this table we also show the relationship of System 1 and System 2 with the "marketing-problem-solving modes" of the ORAC model, to be discussed in Section 3.

In evolutionary terms, System 1, with the dominance of automatic, association-based processes, is an "old" system. System 2 processes of analysis and reasoning make use of parts of the human brain that are of a more recent origin (e.g., the frontal cortex). In System 1, learning takes place through associations and contingencies, is implicit and usually slow. The elements that play a role in System 2 (e.g., concepts, relationships between concepts, models, and computational abilities) can be learned in an explicit way. In principle here learning can go fast.

Traditionally, the analytical approach (System 2) is seen as being more scientific and having a higher intellectual standing. Using intuition (System 1) is sometimes seen as a synonym for sloppy thinking. However, in more recent literature there is a growing recognition of the value of intuition and the power of tacit knowledge. "Intuition is a source of knowledge, a sixth sense, and intuition should be educated" (Hogarth, 2001, p. 23). "Unconscious processes seem to be capable of doing many things that were, not so long ago, thought as requiring mental resources and conscious processes" (Hassin et al., 2005, p. 3). Several empirical studies have shown that individuals can sometimes better follow their intuition than engage in analytical deliberation. Payne et al. (1988) found that under time constraints normative, consciously driven processes can lead to decisions that are worse than the use of more heuristic strategies. Wilson and Schooler (1991) found in an experiment, that respondents (students) did a poorer job in choosing college courses when they were asked to carefully analyze the reasons for their evaluations, than when they made their choices right away. McMackin and Slovic (2000) found that explicit reasoning degraded judgment on an intuitive task, but enhanced predicting on an analytical task. Dijksterhuis (2004) also found that unconscious thinking can lead to better decisions than actively thinking about a problem.

2.4.2 Dual-Process Decision Making in Marketing

Marketing decision making involves both cognitive systems: System 1 *and* System 2. Becoming competent in marketing management requires learning on the spot, a lot of practicing, and accumulating knowledge from experience. This is in the realm of System 1 thinking. Marketing decision making also involves the manipulation of concepts (e.g., thinking about the elements of the marketing mix elements and their effects on sales), reasoning, the development of decision alternatives, abstract thinking, and sometimes, carrying out computations. This is what characterizes System 2 thinking. The eternal discussion in marketing about marketing management as an art or a science is directly related to the distinction between System 1 and System 2 decision making.

At one point in time, there were high expectations about the contribution of the analytical, especially quantitative, approach to the solution of marketing problems. Kotler, in his famous marketing models book (1971, p. 1), wrote "Marketing operations are one of the last phases of business management to come under scientific scrutiny." He observed "the emergence of a new breed of marketing men who are turning to more analytical approaches in response to the increasing pressure on management to tie sales to profits" (p. v). It is true that since the early 1970s, marketing science has tremendously contributed to our body-of-knowledge about marketing phenomena. Yet, marketing management in companies has not evolved into a scientific activity, where thorough analysis and quantification constitute a guarantee for success. Some would say that this is just a matter of time: As our knowledge about marketing phenomena increases and we get better at implementing marketing models in practice, the analytical approach will take over after all.

However, the research findings quoted above suggest otherwise. Although the empirical evidence comes from different domains than marketing, it raises the question whether an analytical approach should always be the preferred way to go. In marketing decision making there can also be situations where intuition dominates analysis. A few experimental studies point in this direction. In a classical study about marketing models Chakravarti et al. (1979) found that respondents using an analytical model, performed worse than respondents who did not use the model. A possible explanation for this result lies in the emerging insight that under certain conditions too much analysis can harm. In a study mentioned before Glazer et al. (1992) found that providing decision makers with specific marketing information (in this case perceptual maps) deteriorated their performance. This probably also was a case of biased decision making where people paid too much attention to the available information, at the cost of taking a more holistic approach which would have been better (Dijksterhuis, 2004, p. 596). Of course, there are also many success stories about the use of analytical decision aids in marketing (Wierenga and Van Bruggen, 2000; Lilien and Rangaswamy, 2004). It is important to identify under which conditions an analytical approach is most successful (possibly reinforced by a matching management support system) and under which conditions intuition provides the best guidance. We will elaborate on this topic in the next section, which discusses the ORAC framework. The ORAC framework distinguishes four different marketing problem-solving modes. Two of them, optimizing and reasoning, resemble System 2 decision making while the other two, analogizing and creating, are System 1 decision making. We will discuss when the different System 1 and System 2 marketing problem-solving modes occur, and what the best matching MMSS are in these situations.

3

The ORAC Model of Marketing Problem-Solving Modes

Marketing management support systems should match with the decision making processes of the marketers that they are supposed to support. Marketers solve problems in different ways. Wierenga and Van Bruggen (2000) developed a taxonomy of the different ways marketers actually approach and solve problems. These ways are called *marketing problem-solving modes*. There are four different marketing problem-solving modes: summarized in the acronym ORAC: optimizing (O), reasoning (R), analogizing (A), and creating (C). In terms of dual-process decision making, as discussed in the previous section, the marketing problem-solving modes optimizing and reasoning are System 2 processes, whereas the marketing problem-solving modes analogizing and creating are System 1 processes. In the following text we give an updated, abbreviated description of the marketing problem-solving modes. The original, full description can be found in Wierenga and Van Bruggen (2000).

3.1 Optimizing

The cognitive model of a marketing manager using the *optimizing* mode is that of a scientist or an engineer who has a clear insight into how marketing processes work. This insight, based on objective knowledge, is represented by a mathematical model, which describes the relationships between the relevant variables in a quantitative way. The decision maker searches for those values of the decision variables that maximize the goal variable(s) for the particular problem. These optimal values for the decision variables are determined in the "model world." Next, they are translated into the "real world." A marketing management problem is converted into a "marketing programming problem" (Kotler, 1971). To solve a marketing programming problem, two basic requirements exist: (1) a model describing the mechanism underlying the marketing problem or phenomenon; *and* (2) an optimization algorithm that searches for the optimal values for the decision variables, given the objective (e.g., profit maximization or increasing brand awareness). In the early days of optimization in marketing, the emphasis was on the optimization *procedure*. If an optimization procedure was available (e.g., linear programming), one was even willing to "adapt" the marketing problem somewhat, so that it would fit the properties of the algorithm (for example, solving media-planning problems with linear programming as discussed before). Afterward, it became clear that it is much more important to have a correct model of the marketing phenomenon under study (since increasing computer capacity has made it practically always possible to carry out the optimization by some form of simulation). This gave rise to a model-building tradition, which became a prominent school in marketing (science). The impressive achievements of the model-building tradition in marketing have been put on record in a series of books: Kotler (1971), Lilien and Kotler (1983), Lilien et al. (1992), Eliashberg and Lilien (1993), and Wierenga (2008a).

For an overall marketing optimization — that is, where all marketing instruments are optimized simultaneously — we would need a "comprehensive marketing system," specifying all the relevant variables and their mutual relationships (Kotler, 1971, p. 667). Although efforts have been made to specify relationships between and within all the subsystems of a comprehensive marketing system (e.g., BRANDAID, Little, 1975), a much more easily achieved goal is to determine the optimum for *one* marketing instrument or at most *a part* of the marketing program. One of the first examples of a "partially" optimizing model is the MEDIAC model for media planning, developed by Little and Lodish (1969). The positive part of the MEDIAC model describes the relationship between the values of the exposure to an advertising campaign, as expressed by the planned insertions in the various media (i.e., a specific media plan). This model can then be used to find the optimal media plan, given the advertising budget on the one hand and the audience and cost data of the available media on the other. The planning of sales-force operations (e.g., CALLPLAN, Lodish, 1971) and supermarket shelf-space allocation (e.g., SH.A.R.P. Bultez and Naert, 1988) are other domains where the optimizing mode has been successfully applied. The features of the optimizing mode as well as of the other marketing problem-solving modes are summarized in Table 3.1.

Table 3.1. The four marketing problem-solving modes (ORAC) and their link to dual-process decision making.

System 1: Analytical cognitive processes
Optimizing
Strongly structured problems based on objective knowledge
Underlying mechanism of the phenomena is known
Analytical/mathematical approach
Clear objective function
Best solution exists and can be found
Reasoning
DM has structured the problem in the mind
This (mental) model includes the relevant variables and the cause–effect relations
It can be based on facts and/or subjective assumptions
The model is often incomplete, but may contain deep knowledge
Decision making is typically based on if-then statements
System 2: Intuitive cognitive processes
Analogizing
Weakly structured problems
No clear objective function, nor a clear set of relevant variables
Decisions base on similarity with earlier problems (pattern recognition)
Recognition may be conscious or non-conscious (intuition)
Undeep knowledge
Creating
Unstructured problems
Exploration and transformation of the problem space
Associations
Divergent thinking
New combinations

3.2 Reasoning

The fact that individuals form and use mental representations of phenomena in the outside world has long been recognized. Such representations are called "mental models." Mental models are symbolic structures, a representation of a body-of-knowledge in the human mind (Johnson-Laird, 1988, 1989). A person can use such a mental model for reasoning about a phenomenon. In cognitive science this type of approach to a problem is called "model-based reasoning" (Hayes, 1985; Forbus, 1988; Johnson-Laird, 1989). Mental models have generated considerable interest and the concept has been used in different domains. Sometimes at the fundamental level of human perception — for example, the mental representation of a word, a geometric figure, or language comprehension (Anderson, 1983; Johnson-Laird, 1988) — but also to describe how humans deal mentally with complex phenomena. Examples are mental models for physical systems such as the working of a calculator (Gentner and Stevens, 1983), mental models that underlie public policy decisions (Axelrod, 1976), managerial mental models (Courtney et al., 1987; Day and Nedungadi, 1994), and mental models that form the basis for strategic planning and subjective forecasting (Klayman and Schoemaker, 1993).

In the absence of an objective model, a marketer often adopts a marketing problem-solving mode called *reasoning*. In the optimizing mode it is assumed that there is an objective model that provides a valid description of the marketing phenomenon under study. However, only a small part of all marketing phenomena has been brought under scientific scrutiny, and our systematic, scientifically based knowledge of marketing phenomena is limited. So if a systematic world underlying marketing phenomena exists at all, it has been explored and mapped out only incompletely. In the reasoning mode, decision makers construct a representation of the marketing phenomenon in their minds. These mental models are the basis for the manager's reasoning about the problem. This reasoning often takes the form of if-then statements. For example: if this is a new brand, then we have to create brand awareness among customers. A mental model consists of variables deemed relevant and the supposed cause-and-effect relationships between these variables. It helps a decision maker to diagnose and solve a specific problem.

Mental models can be based on facts, but also on subjective assumptions. Therefore, different marketing managers may have different mental models with respect to the same phenomenon. For example, in the case of advertising, different marketing managers may use different models to explain why a particular advertising campaign was successful. A marketer's mental model of a specific phenomenon is shaped by experience in practice, sometimes after a theoretical education. Compared with the marketing model used in the optimizing model, the mental model in the reasoning mode is more qualitative, subjective, and incomplete.

Mental models can and will often be at variance with reality. In physics many examples exist of mental models that proved to be wrong after thorough scientific examination. For example, the idea that heat and temperature are the same concept has existed among scientists for centuries and was only replaced by the correct model around 1750. It turned out that heat and temperature are different kinds of physical entities, that is adding a given quantity of heat does not yield a fixed increase of temperature (Wiser and Carey, 1983). Although mental models may not always be correct, they are useful because they offer the marketer a framework for interpreting and reasoning about marketing problems and their solutions. As long as the truly objective and accurate scientific model is lacking, mental models have to be used. These mental models will be updated (and hopefully improve) over time, based on the feedback from the decisions in the marketplace.

3.3 Analogizing

When confronted with a problem, a person has a natural inclination to bring to bear the experiences gained from solving similar problems. A doctor, faced with a patient with an unusual combination of symptoms, may remember another patient with similar symptoms and propose the same diagnosis as in the previous case (Kolodner, 1993). Analogizing is considered a fundamental mechanism in human understanding and problem solving. "Analogy-making lies at the heart of intelligence" (Hofstadter, 1995, p. 63). Children automatically apply analogical thinking, and some elements of analogical thinking can even be found in apes and chimpanzees (Holyak and Thagard, 1995).

For a long time the "general problem-solving" school was dominant in cognitive science. According to this school, human thought depends on a set of reasoning principles that are independent of any given domain — meaning that we (human beings) reason the same way no matter what we are reasoning on. Simon (1979, p. xii) formulated this (standard) way of operating by "Thinking Man" as follows: "Thinking is a process of serial selective search through large spaces of alternatives guided by individual mechanisms that operate through dynamically adapting aspiration levels." However, the proponents of analogical reasoning have a very different view (Riesbeck and Schank, 1989, p. 3): "Certain aspects of human thought may be a simpler affair than many scientists have imagined." In other words, human problem-solving behavior can often be explained by much simpler mechanisms than the general problem solver.

Analogical (or "cased-based") reasoning implies that the *original concrete instances* are used for reasoning, rather than abstractions based on those instances. One might deduce general principles from the experienced cases, but according to Riesbeck and Schank, such "general principles are impoverished compared to the original experience." After many repetitions of the same situation, some cases may be "coalescing" into rules. However, these rules are encoded in memory separate from any particular instance of their use or the history of their creation. Analogical reasoning is based on pattern recognition. Recognition may be conscious or non-conscious. In the latter case we can speak of intuition (Simon, 1995).

Wide support exists for analogical reasoning as a model for human decision making. Studies in human problem solving reveal the pervasiveness of analogy usage (Sternberg, 1977). People find analogical reasoning a natural way to reason. Car mechanics, physicians, architects, and caterers use it. In particular, case-based reasoning excels as an approach to "weak-theory domains," domains where phenomena are not understood well enough to determine causality unambiguously (Kolodner, 1993).

Indeed, much of marketing problem solving probably follows the analogizing path. A marketing manager usually has a set of experiences (cases) available in memory, referring to all kinds of marketing events: new product introductions, price changes, sales promotions, advertising campaigns, reactions of competitors, and so on. In a new situation, even without active effort on the part of the manager, one or more earlier situations come to mind resembling the current one. Sometimes, the manager will choose the same kind of solution as in the previous case. For example, a manager may decide to execute the same sales promotion for a product in country B as the earlier one that was so successful in country A. However, in many cases the manager will not literally repeat the previous solution but will adapt it somewhat. In a sales promotion, for example, the specific premium and packaging used in country B may differ from those used in country A. Hoch and Schkade (1996) found that to arrive at a forecast, decision makers often search their experience for a situation similar to the one at hand, and then make small adjustments to that previous situation.

Basically, in these situations a process of *analogizing* or *analogical reasoning* takes place. For most problems, marketing theory is insufficient ("weak-theory domain"). Often, marketing managers also have no generalized rules available that are drawn from experience and that can serve as elements of a mental model. However, managers do have a lot of experience with more or less similar cases. Managers tend to think in cases and "stories" (Goldstein, 2001). Moreover, in many instances there simply is not enough time to solve a problem by reasoning from "first principles" — that is, to build a (mental) model that explains a phenomenon in terms of elementary events. Analogical reasoning then is a fast and practical way of problem solving.

3.4 Creating

The last marketing problem-solving mode that we distinguish is creating. Using the creating mode, a marketing decision maker searches for concepts, solutions, or ideas that are novel in responding to a situation that has not occurred before. However, what precisely is a creative idea, and how do marketers hit upon those ideas that really make a difference in the marketplace? What was the creative process that led to successes like Post-it, the famous yellow pieces of paper from 3M, or the catchy brand name Q8, of Kuwait Petroleum?

The literal (dictionary) meaning of *create* is "to bring into being or form out of nothing." Ackoff and Vergara (1981) define creativity (in a management context) as "the ability to break through constraints imposed by habit and tradition so as to find new solutions to problems." This formulation makes clear that creating means stepping away from the conventional path. Creativity implies "divergent thinking" — that is, thinking with an open mind, expanding the set of decision possibilities, enlarging the solution space — which is the opposite of "convergent thinking" — that is, the evaluation and screening of existing possibilities (Chung, 1987). This divergent thinking has also been referred to as "restructuring the whole situation" (Wertheimer, 1959), "reframing" (Russo and Schoemaker, 1990) and "transformation of conceptual spaces" (Boden, 1991). However, divergent thinking is not a sufficient condition to explain creativity. The element of problem finding, problem discovery, or "sensing gaps," is also important (Kabanoff and Rossiter, 1994). Creativity often means coming up with solutions for problems that one was not aware of. In the management literature there are several references to this concept of problem finding (Pounds, 1969; Courtney et al., 1987; Smith, 1989).

Elam and Mead (1990) emphasize the new-combination character of creative ideas: "Creativity involves combining known but previously unrelated facts and ideas in such a way that new ones emerge." Boden (1994) defines and explains creativity "in terms of the mapping, exploration, and transformation of structured conceptual spaces." In the more applied literature, elements of value and usefulness are often part of the definition of creative output. MacCrimmon and Wagner (1994) mention the dimensions of novelty, nonobviousness, workability, relevance, and thoroughness. Bruner (1962) defines creativity as an act that produces "effective surprise." One aspect that is found in many theoretical contributions, as well as in the thinking processes of very creative persons, is that of "making connections" (MacCrimmon and Wagner, 1994). This means the creation of new ideas through the association of existing ones (related to the "new-combinations" concept mentioned earlier).

It is widely accepted that marketing requires a good deal of creativity. Marketing problems are often not well defined in terms of goals, means, mechanisms, and constraints, and often do not lend themselves to the procedural or logical reasoning in conventional computer programs or knowledge-based systems. The cognitive model of a marketer following the creating mode is one of a decision maker who — consciously or unconsciously, by means of mapping, exploring, and transforming conceptual space, expanding the number of possible solutions through divergent thinking, and making connections and associations — is searching for novel and effective ideas and solutions to strengthen the market position of the product, brand, or company. Creating can refer to all aspects of the marketing management domain, including generating ideas for new products or services, innovative advertising or sales-promotion campaigns, new forms of distribution, and ingenious pricing. Creativity is an important asset. Many companies owe their existence to a creative new product or process, and creativity is often the means for survival as well as growth.

There is overlap between the creating and analogizing modes. For example, analogies can be a source of creativity: a metaphor can be a springboard for creative solutions (Tardiff and Sternberg, 1988) and can generate mental leaps (Holyak and Thagard, 1995). The usefulness of analogies for creative solutions in marketing has been demonstrated by Althuizen and Wierenga (2010).

3.5 Drivers of Marketing Problem-Solving Modes

The marketing problem-solving mode used by a decision maker depends on a number of factors. The most important factors are: (i) characteristics of the marketing problem; (ii) characteristics of the decision maker; and (iii) characteristics of the decision environment.

3.5.1 Marketing Problem Characteristics

This section discusses marketing problem characteristics and pays attention to four important elements: the structuredness of the problem, the depth of available knowledge, the availability of data, and the frequency of the decision. Of course, these elements are mutually related.

Structuredness of the problem concerns the extent to which relevant elements of a problem and the relationships between those elements are known. Structuredness of a management problem has received a lot of attention in the literature (Keen and Scott Morton, 1978; Sprague, 1989). The concept goes back to Simon's (1960) notion of "programmability." For the optimizing mode, a high level of structuredness is required. Examples of relatively programmable and structured marketing problems are sales management and sales force decisions, and media planning for advertising. An example of a much less structured problem is inventing a brand name for a new product. Such a problem requires (sometimes) analogizing and (certainly) creating.

Depth of knowledge refers to generalized knowledge — that is, the product of scientific research. For this subject also the term "completeness of knowledge" has been used (Rangaswamy et al., 1989). The optimizing mode requires deep knowledge. However, the required depth of knowledge (in the sense of objective, scientifically verified knowledge) decreases in the direction of reasoning, analogizing, and creating.

Data availability is necessary for developing mathematical (optimizing) models. Data also play an important role in the formation of a marketer's mental model, used in the reasoning mode. Data helps to form an impression of the mechanisms in a market. For analogizing and creating, however, the cognitive processes are more qualitative and subjective.

The *frequency of occurring* is also an important marketing problem characteristic. Broadly speaking we can make a difference between two categories of decisions and managerial activities. The first category is (relatively) unique decisions that are made infrequently, are highly important, and that will be determining for the long-term position of the company in the markets it is operating in. Examples of these decisions are strategic decisions about which markets to enter, the positioning of a new product and which customers to target with such a product. For such "new" decisions the decision process is intensive and lengthy. Decision makers will have to come up with the relevant variables that need to be included in the decision process and how these variables re related to each other and to marketing performance metrics. The second category deals with more common decisions and activities that take place on an almost continuous basis. For example, many online retailers provide customized offers to visitors of their stores as soon as these visitors enter the store and are identified.

3.5.2 Decision Maker Characteristics

Not all marketing decision makers are created the same. The specific characteristics of marketers affect the way they approach problems and make decisions. We discuss four important decision maker characteristics: cognitive style, experience, education, and skills.

The *cognitive style* of decision makers refers to the process through which they perceive and process information. Most common is the classification of decision makers into two categories, i.e., analytical and non-analytical. Sometimes the adjectives systematic and heuristic are also used to indicate these two classes (Bariff and Lusk, 1977; Zmud, 1979). Analytical decision makers reduce a problem to a core set of underlying relationships. All effort is directed toward detecting these relationships and manipulating the decision variables in such a manner that some "optimal" equilibrium is reached with respect to the objectives. Non-analytical decision makers look for workable solutions to total problem situations. They search for analogies with familiar, solved problems. Common sense, intuition, and un-quantified "feelings" play an important role (Huysmans, 1970). All other things being equal, analytical decision makers will tend toward the optimizing and reasoning modes, while non-analytical decision makers will be inclined to use analogizing or creating.

A high degree of marketing decision making *experience* means that a person has dealt with a large number of practical marketing problems and their solutions. This provides the marketer with the opportunity to develop a rich mental model, which favors the reasoning mode. On the other hand, all these experiences also constitute many cases, which can serve as a basis for analogizing. Which of the two modes the experienced decision maker will tend to use — reasoning or analogizing — may well depend on the individual's cognitive style, with analytical types tending toward reasoning and non-analytical types toward analogizing.

An academic *education* stimulates an analytical approach, favoring optimizing and reasoning. Little (1979b) expected that the use of marketing decision support systems would benefit from the influx on model-trained graduates in companies. Other educational institutions (for example, professional and trade schools) emphasize examples and case histories. Consequently, all other factors being equal, their graduates are more conditioned toward analogizing and creating.

Skills will facilitate the use of a certain mode. For example, quantitative skills stimulate the optimizing mode. Persons who are actively surfing the Internet may be more disposed to analogizing and creating. People can be trained to develop specific skills, for example to become more creative.

3.5.3 Characteristics of the Decision Environment

The characteristics of the decision environment affect the way marketing managers make decisions and thereby the dominant marketing problem-solving mode in a particular decision situation. Important decision environment characteristics are time constraints, the amount of market dynamics, and the organizational culture.

Time pressure will often preclude rational decision making by passing through the complete sequence of model specification, parameter estimation, and using the model for optimizing. Several causes exist for the shortage of time a manager often experiences when making decisions. Internal causes originate from the way a company is organized, e.g., fixed reporting schedules, deadlines for proposals and the fact that mostly a marketer has to divide attention between many products and brands. There are also external causes of time pressure, the most important of which is competition. Being first, the pre-emptive move is often more important than developing the perfect plan, but implementing it too late. When time is short, the quickest way to solve a problem is to consult one's memory and to search for similar cases experienced before. Time pressure works in favor of the analogizing mode. Some amount of reasoning can also occur, but this will be confined to the marketer's consulting of the existing mental model. Time pressure is not conducive to creativity because creativity takes time (Tardiff and Sternberg, 1988), and deadlines are detrimental to creativity (Hennesey and Amabile, 1988).

Marketing dynamics is important too. There is a big difference between operating in a stable market and operating in a turbulent one (e.g., compare the coffee market (Simon, 1994) with the market for IT-driven products). In stable markets mathematical models are better usable, implying that in those situations, the optimizing mode will be used more often. Under turbulent market conditions, however, marketers will be hard-pressed to understand and interpret what is going on and constantly revise their mental models of the market. If mathematical models would be feasible at all, they would have to be re-specified and re-estimated all the time. So in dynamic market conditions we expect that the reasoning mode will be used more often. Turbulence is also conducive to the creating mode (e.g., see the current innovations related to the Internet).

Finally, there is the *organizational culture*. A company or department will have certain prevailing attitudes and a certain "standard" approach to doing things and certain prevailing attitudes (Pettigrew, 1979). If in a company in general there is a positive attitude toward quantitative analyses and the use of models, this will extend to the way marketing managers go about problem solving in their domain — favoring the optimizing and reasoning modes. Similarly, more heuristic/holistic cultural attitudes favor analogizing and creating. Organizations also make assumptions about the "analyzability" of their environment. If an organization believes that its environment is analyzable, it will try to grasp the underlying patterns through analysis, and will use techniques such as correlation and forecasting. If an organization believes that its environment is not analyzable, it will rely more on soft, qualitative data, judgment, and intuition (Daft and Weick, 1984).

3.5.3.1 Changes in the working environment of the marketer

Thirty years ago, Little (1979b, p. 23) observed that computers "are impossible to work with" and he foresaw the need for "marketing science intermediaries," professionals with good technical skills who would bridge the gap between the computer and the manager. Through the spectacular developments in information technology, the reality of today is completely different. The computer is now the most intimate business partner of the manager. Whether it is in the form of a desktop PC, a laptop, a PDA, or a Smartphone, the computer is completely integrated in the marketer's daily work. A study among German managers reported that managers spend on average 10.3 hours per week using information technology (Vlahos et al., 2004), that is about 25% of their work time. The comparable figure for the United States is 11.1 hours per week and for Greece 9.3 hours (Ferrat and Vlahos, 1998). Marketing and sales managers spend on average 8.6 hours per week using the computer (a bit lower than the 10.3 hours overall), which makes it clear that for marketers the computer is now a key element of the job. Today, a marketer typically has access to several databases and programs that monitor (customer) sales, market shares, distribution, marketing activities, actions of competitors and other relevant items. Such systems are either made in-house, i.e., by the firm's own IT department, or made available by third parties. Providers of syndicated data, such as Nielsen, IRI, and GfK, typically make software available for going through databases, and for specific analyses. For the adoption and use of MMSS it is an important advantage that marketing managers are fully connected to an IT platform. When an MMSS is introduced, the "distribution channel" to the marketing manager (i.e., the platform) is already there. In this way, using the MMSS becomes a natural part of the (daily) interaction with the computer. One step further, marketing decision support tools are not separate programs anymore, but have become completely embedded in other IT systems that managers use (see also Lilien and Rangaswamy, 2008). Most of the times these systems will be web-based.

For a successful implementation and use of MMSS, the relationship between the marketing department and the IT/IS department in a company is critical. There are indications that the power balance between marketing and the firm's overall information department is changing in favor of marketing. In a study among managers of market research in *Fortune 500* companies, Li et al. (2001) concluded that marketing

Table 3.2. Conditions conductive to adopting a specific marketing problem-solving mode.

	Optimizing	**Reasoning**	**Analogizing**	**Creating**
Problem	High structuredness	Moderate stucturedness	Low structuredness	No precise problem formulation
	Precise knowledge of relationships	Knowledge of most important variables	Weak theory	No theory
	Quantitative data	Quantitative or qualitative data	Experiences/cases	Remote associations
Decision maker	Analytical decision maker	Analytical decision maker	Heuristic decision maker	Heuristic decision maker
	-	Experienced decision maker	Experienced decision maker	No specific education
	Academic Education	Academic education	MBA/Professional education	No quantitative skills
	Quantitative skills	Quantitative skills	No quantitative skills	Creative skills and intrinsic motivation
Environment	Ample time frame	Limited time frame	Little time available	No time pressure
	Stable market	Dynamic market	Dynamic	Dynamic market
	Quantitative/analytical attitude in company	Analytical attitude in company	Heuristic/holistic attitude in company	Heuristic/holistic attitude in company

has an increasing influence on the company plan for strategic information resources and that marketing now occupies a "position of power in the organization in terms of computer use with marketing generally calling the shots" (p. 319). This is a big change from the early days of computers in companies, when marketing occupied one of the last places in the IT priority queue, after accounting, finance, production, and operations.

This concludes our discussion of the drivers of the marketing problem-solving modes. Table 3.2 presents a summary of how the problem characteristics, the decision maker characteristics, and the decision maker environment characteristics influence the likelihood of a specific marketing problem-solving mode to become selected.

4

Marketing Management Support Systems (MMSS)

Our definition of marketing management support systems is as follows (Wierenga and Van Bruggen, 2000):

> *Any device combining (1) information technology, (2) analytical capabilities, (3) marketing data, and (4) marketing knowledge, made available to one or more marketing decision maker(s) with the objective to improve the quality of marketing management.*

4.1 The Components of Marketing Management Support Systems

Marketing management support systems thus constitute a combination of four components (see Figure 4.1):

(1) Different elements of *Information Technology*, both hardware (e.g., computers, PCs, workstations, optical scanning technology, networks, etc.) and software (e.g., database management programs, programming languages, software development environments, spreadsheets, graphics, communication software, and so on).

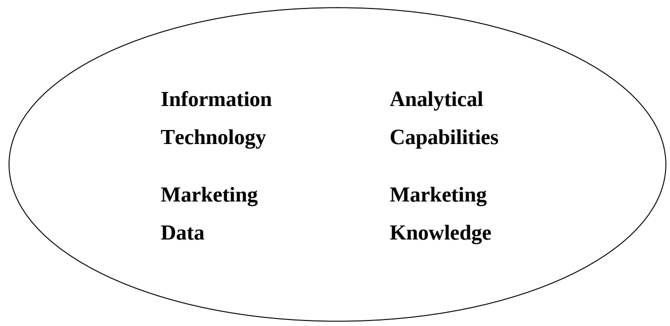

Fig. 4.1 The components of marketing management support systems.

(2) *Analytical Capabilities*, which can take many different forms: statistical packages for analyzing marketing data, parameter-estimation procedures, marketing models, and simulation and optimization procedures.
(3) *Marketing Data*: quantitative information about variables such as sales, market shares, prices, own and one's competitors' marketing-mix expenditures, distribution figures, and so on.
(4) *Marketing Knowledge* — that is, qualitative knowledge about such things as the structure of markets or market segments, the suitability of specific sales-promotion campaigns, typical reactions to advertisements, heuristics for the acceptance of clients, and so on.

4.2 Different Types of Marketing Management Support Systems

The term Marketing Management Support Systems is a collective noun for a variety of systems that have been developed since the early 1960s. Table 4.1 presents an overview of the different types of marketing management support systems.

Marketing models mark the start of the use of econometrics and operations research in marketing decision making, strongly stimulated by the advent of computers in companies. Mathematical

Table 4.1. Overview of the different types of marketing management support systems.

Type of MMSS	Characterizing Keywords
Marketing Models (MM)	— Mathematical representation — Optimal values for marketing instruments — Objective — Best solution
Marketing Information Systems (MKIS)	— Storage and retrieval of data — Quantitative information — Registration of "what happens in the market" — Passive systems
Customer Relationship Management (CRM) Systems	— Data of individual customers — Customer characteristics — Interactions and purchase history — Profit potential/lifetime value — Predictive modeling and data mining
Marketing Dashboards (MDB)	— Key performance metrics — Single visual display — Integrative role — Drill-down possibilities
Marketing Decision Support Systems (MDSS)	— Flexible systems — Recognition of managerial judgment — Able to answer "why" questions (analysis) and "what-if" questions (simulation)
Marketing Expert Systems (MES)	— Centers on marketing knowledge — Human experts — Rule-based knowledge representation — Normative approach: best solution
Marketing Knowledge-Based Systems (MKBS)	— Diversity of methods, including hybrid approaches — Structured knowledge representation, including frame-based hierarchies — Model-based reasoning
Marketing Case-Based Reasoning Systems (MCBR)	— Similarity with earlier cases — Storage of cases in memory — Retrieval and adaptation — No generalization
Marketing Neural Networks (MNN)	— Training of associations — Pattern recognition — No a priori theory — Learning

representations of marketing problems are developed, with the aim of finding optimal values for marketing instruments. The philosophy underlying these systems is that it is possible to find the objectively best solution. From the mid-1960s onward, marketers use *marketing information systems* for 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 what possible causes of these events are. Whereas the first marketing information systems primarily dealt with variables at the aggregate level (e.g., sales, advertising expenditures, market share) a new type of MMSS has its focus on the individual customer. These systems are called *Customer Relationship Management (CRM) systems.* CRM systems not only store customer characteristics data, but also data on interactions with the customer, the customer's purchase history, and profit potential (customer lifetime value). Another, new[1] type of marketing decision support systems, which can also be considered as a recent offspring from marketing information systems, are *marketing dashboards (MDB*). Marketing dashboards have primarily been developed to help the manager cope with the large amount information (s)he is confronted with. An MDB provides the key marketing performance metrics in one visual display, so that the user can gauge the situation in the blink of an eye. Marketing dashboards also have an integrating role in that they connect the marketing metrics to the bottom-line financial results of the company. Individual users of an MDB can always drill down to more specific performance information, for example about certain brands or geographic areas. Whereas marketing information systems are relatively passive systems that provide marketers only with the information they are looking for, *marketing decision support systems* are more active. They provide marketers with the opportunity to answer "what-if" questions by means of making simulations. Contrary to marketing models, the goal of marketing decision support systems is not to replace but to support the marketer. Using judgment, marketers generate ideas for possible courses of action and

[1] We pay more extensive attention to the new types of marketing management support systems on the list of Table 2.2, CRM systems and marketing dashboards, in Section 2.5.

with the help of the marketing decision support system the outcomes of these actions can be predicted. However, in the end the marketer's judgment will be the decisive factor in selecting the final and most appropriate course of action.

The mid-1980s brought a new generation of management of marketing management support systems. These systems emphasized the marketing knowledge component rather than quantitative data. *Marketing expert systems* were the first type of these knowledge-based systems. The basic philosophy underlying these systems is to capture the knowledge from an expert in a specific domain and make that knowledge available in a computer program for solving problems in that domain. The goal of an expert system is to replicate the performance levels of (a) human experts in a computer model (Rangaswamy, 1993). These systems take a normative approach in that they search for the "best" solution for a given problem. *Marketing knowledge-based systems*, introduced in the early 1990s, refer to broader class of systems than marketing expert systems do. They obtain their knowledge from any source, not just form human experts but also from textbooks, cases, and so on. Furthermore, knowledge can be represented in multiple forms, i.e., not only by means of rules as in expert systems but also by means of semantic networks and frame-based hierarchies. Contrary to marketing expert systems, knowledge-based systems do not focus on finding a best solution but emphasize the reasoning processes of decision makers. The third type of knowledge-based systems, *marketing case-based reasoning systems*, first appeared in the mid-1990s. These systems focus on the support of reasoning by analogies. Analogical reasoning is a way of solving problems in which solutions to similar problems in the past are taken as a starting point for a solution to current problems. Marketing case-based reasoning systems make cases available in a case library and provide tools for retrieving an accessing these.

Marketing neural networks are systems that reproduce the way human beings attach meaning to a set of incoming stimuli in a computer, that is, how people recognize patterns form signals. These systems resemble the actual physical process that takes place in the human brain, where incoming signals are transmitted through a massive network of connections, which are formed by links among neurons in the brain. Through this process a human being is able to recognize patterns in sets of incoming stimuli, i.e., a specific output is connected to input. Neural networks have become very prominent in the area of predictive modeling, where networks are trained to learn the associations between data about customers (including their purchase histories) and the probability of specific behavior (for example, buying of a particular product).

Marketing creativity support systems are computer programs that stimulate and endorse the creativity of marketing decision makers. Although the number of creativity-enhancement programs developed so far is limited, we expect these systems to become more popular in the coming years, given the increasing importance of creativity in marketing, for example for the development of new products or innovative marketing communication campaigns. The extent to which the four components of MMSS are present in the various types of MMSS differs. For example, marketing models are heavily leaning toward analytical capabilities, whereas in marketing expert systems information technology and marketing knowledge are the main components. Figure 4.2

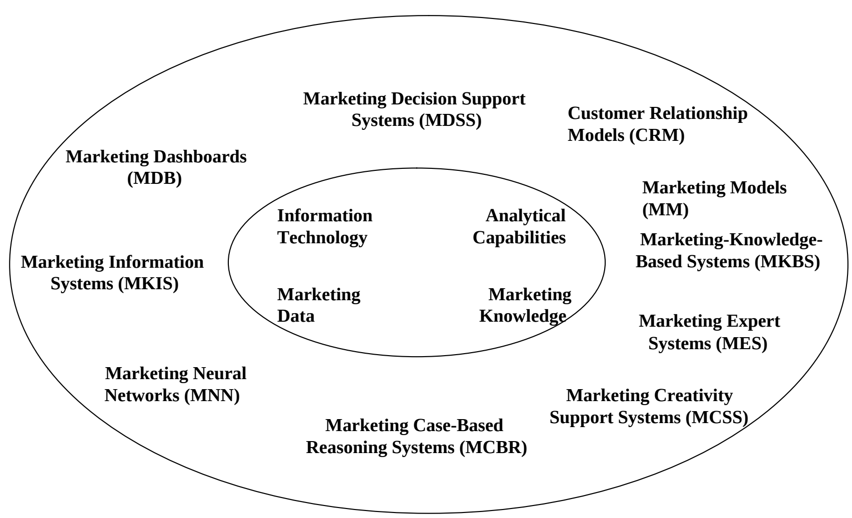

Fig. 4.2 The constituting components and different types of marketing management support systems.

shows the different types of MMSS and how they are related to the four components.

In the following two sections we discuss the developments in two key decision support technologies, which are very important for marketing: marketing models and artificial intelligence. Following, we discuss two new types of marketing management support systems: customer relationship management (CRM) systems and marketing dashboards.

4.3 Developments in Marketing Models[2]

Marketing management support systems derive their analytical capabilities from the use of marketing models. Models entered the field of marketing in the 1960s. Stimulating factors at that time were the advances in econometrics and operations research, the two fields that constitute the scientific basis of marketing models. Also the arrival of (mainframe) computers contributed a lot to the development of marketing models. From its modest beginning marketing models have developed into one of the main fields of the marketing discipline. Table 4.2, taken from Wierenga (2008a), sketches the development of marketing models over the last five decades. It started with the application of OR techniques to marketing problems: optimization methods (for example, linear programming and goal programming), Markov models, simulation techniques, and game theory (Montgomery and Urban, 1969).

The next decade, the 1970s deserves the title of "The Golden Decade" for marketing models. In this period, the field of marketing models grew exponentially and developed an identity of its own. The modeling of marketing phenomena and marketing problems became interesting in itself, irrespective of whether or not they could be solved with a known OR technique. The development of marketing models as a field in itself has continued since then. As Table 4.2 shows, the 1970s produced a rich variety of modeling approaches, such as stochastic models (especially consumer brand choice models), models for specific marketing mix instruments (e.g., models for advertising, pricing, and personal selling), and so-called sales response models describing the

[2] This section is based on Wierenga, B. Ed. (2008a), *Handbook of Marketing Decision Models.* New York: Springer.

Table 4.2. Marketing decision models in five decades.

Period	Prominent Approaches	Representative Examples/ References
1960–1969 *The Beginning*	• Micro-economic approaches to marketing problems • Marketing problems formulated as known operation research (OR) problems	• Dorfman and Steiner (1954); Nerlove and Arrow (1962); Vidale and Wolfe (1957) • Engel and Warshaw (1964); Montgomery and Urban (1969, 1970)
1970–1979 *The Golden Decade*	• Stochastic Models • Models for marketing instruments • Market response models • Labeled marketing decision models • Marketing decision support systems	• Massy et al. (1970); • Kotler (1971) • Clarke (1976); Little (1979a) • CALLPLAN (Lodish, 1971); ASSESSOR (Silk and Urban, 1978) ADMOD (Aaker, 1975); • Little (1979b)
1980–1989 *Toward Generalizations and Marketing Knowledge*	• Meta-analyses of the effects of marketing instruments • Knowledge-based models and expert systems • Conjoint analysis models	• Asmus et al. (1984); Tellis (1988) • PROMOTER (Abraham and Lodish, 1987); ADCAD (Burke et al., 1990); McCann and Gallagher (1990) • Green et al. (1981)
1990–1999 *The Marketing Information Revolution*	• Scanner-data-based consumer choice modeling • Neural nets and data mining • Stylized theoretical modeling	• Neslin (1990); Chintagunta et al. (1991); Abraham and Lodish (1993) • Hruschka (1993); West et al. (1997) • Moorthy (1993); Choi (1991); Kim and Staelin (1999)
2000- *The Customer-centric Approach*	• Customer Relationship Management (CRM) models • Customer Lifetime Value (CLV) models • Electronic Commerce Models	• Reinartz and Kumar (2000); Reinartz et al. (2005); Hardie et al. (2005) • Gupta et al. (2004) • Chatterjee et al. (2003); Ansari and Mela (2003); Bucklin and Sismeiro (2003); Moe and Fader (2004)

relationship between a particular marketing instrument and sales. For the estimation of response functions from empirical data, econometrics became increasingly important.

In the 1970s we also observe the take-off of so-called "labeled models". A labeled model typically works in three steps: (i) a specific mathematical structure (model) for a particular marketing phenomenon is proposed; (ii) this model is coded in a computer program; and (iii) this program is used for marketing decision making, for example for predicting the outcomes of alternative marketing actions or optimizing marketing efforts. It became fashionable to give a specific label or name to such a model, often an acronym that expressed its purpose. Well-known examples are: CALLPLAN (Lodish, 1971) for the planning of sales call decisions, ADMOD (Aaker, 1975) for media planning in advertising, and ASSESSOR (Silk and Urban, 1978) for new product decisions. Many of these labels have become "icons" in the marketing models field.

Another significant development in the 1970s was the emergence of the concept of "Marketing Decision Support Systems" (MDSS) (Little, 1979b). The purpose of MDSS is to bridge the distance between the (often) abstract marketing models and the reality of marketing decision making in practice. Practical marketing problems often are not very well-structured, and MDSS are particularly suitable for dealing with less- or semi-structured problems. The first work on marketing decision support systems in the 1970s has been succeeded by a lot of subsequent research on the issue of how marketing models can really have an impact on marketing decision making in practice, including this issue of Foundations and Trends in Marketing.

By the 1980s the work on marketing response models had produced sufficient studies for making generalizations, based on meta-analyses. During this decade marketing knowledge as such became a popular topic, which gave rise to the development of (AI-based) knowledge-based systems and marketing expert systems. As a separate development, in this decade conjoint analysis models became quite prominent, which have remained an extremely versatile decision analysis tool until today.

The 1990s is the decade in which (point-of-purchase) scanner data became available on a large scale. This "marketing information revolution" (Blattberg et al., 1994) was a major driver of a surge in consumer choice modeling, especially in the area of sales promotions. Multinomial logit models (Guadagni and Little, 1983) were used as the most prominent tool to carry out this work. The topics studied included the construction of baseline sales levels, the effects of different sales promotion instruments on sales, the effects of heterogeneity in the consumer population, and the decomposition of the sales promotion "bump" into components, such as brand switching, purchase time acceleration, and stockpiling (Gupta, 1988). The quickly growing amounts of data also made it possible to employ new techniques from artificial intelligence and computer science. These are inductive techniques (e.g., artificial neural nets) searching for regularities in large databases, and in this way "extracting" knowledge from data. These methods, often referred to as "data mining", emerged in marketing in the 1990s, and with the ever growing power of computers and the ever larger databases, will become even more important in the future.

The most important development in the *first decade of the current millennium* is that individual customers have become the unit of analysis. Enabled by the strongly increased storage capacity, companies have set up (often huge) databases with records of individual customers. Mostly, these databases are part of Customer Relationship Management (CRM) systems. The emphasis on individual customers has been amplified by the advent of e-commerce or online marketing. Online marketing has dramatically changed the way suppliers interact with their customers. Here also a new category of models is emerging: electronic commerce models, for example models for the attraction of visitors to a site, models for banner ad response, and models for paid search advertising (Bucklin, 2008). The movement toward the individual customer and online marketing has again generated enormous amounts of new data: CRM data, clickstream data, and electronic commerce data. We can speak of a "second marketing information revolution", which continues until today.

4.4 Artificial Intelligence (AI) and Marketing

To date, data-driven approaches, mostly a combination of econometric methods and operations research are dominant in marketing management support systems. It is safe to say that data-driven, quantitative models make up for over 80% of all the work on decision support systems in marketing. Quantitative models are particularly useful for well-structured problems. However, many marketing problems are not that well-structured and judgment, expertise, and intuition are required to solve them. Quantitative models are less useful in these instances. This is where tools and methods developed in the field of artificial intelligence (AI) come in. Artificial intelligence builds programs of human thought and decision processes that can be executed by computers. In 1958 Simon and Newell, two of the founding fathers of AI, wrote that "the very core of managerial activity is the exercise of judgment and intuition" and "large areas of managerial activity have hardly been touched by operations and management science" (Simon and Newell, 1958). In the same paper (in Operations Research) they foresaw the day that it would be possible "to handle with appropriate analytical tools the problems that we now tackle with judgment and guess". Simon (1997) emphasized the limited cognitive capabilities of decision makers and concepts that he invented such as *bounded rationality* and *satisficing versus optimizing* became very influential in management, including marketing. Since its beginning in the 1950s, the field of artificial intelligence has developed into a substantive discipline with a broad variety of approaches that can be used in decision making, especially for less structured problems. The main applications of AI in marketing, so far, are expert systems, neural nets, and case-based reasoning. We discuss these briefly in the following.

4.4.1 Expert Systems

In the late 1980s, knowledge emerged as a major topic together with the notion that knowledge can be captured and subsequently used in so-called knowledge-based systems. In marketing, this created a wave of interest in expert systems. Expert systems were developed for several domains of marketing (McCann and Gallagher, 1990). For example, (i) to find the most suitable type of sales promotion; (ii) to recommend the execution of advertisements (positioning, message, presenter); (iii) to screen new product ideas; and (iv) to automate the interpretation of scanner data, including writing reports. In the late

1980s, over twenty expert systems were published in the marketing literature (Wierenga and Van Bruggen, 2000, Chapter 5). An example of a system especially developed for supporting a particular marketing function is BRANDFRAME (Wierenga et al., 2000; Wierenga and Van Bruggen, 2001). This system supports the decision making of a product or brand manager, which is a typical marketing job.

4.4.2 Neural Networks and Predictive Modeling

Around 2000, customer relationship management (CRM) became an important topic in marketing. An essential element of CRM (which is closely related to direct marketing) is the customer database which contains information about each individual customer. This information may refer to socio-economic characteristics (age, gender, education, income), earlier interactions with the customer (e.g., offers made and responses to these offers, complaints, service), and information about the purchase history of the customer (i.e., how much purchased and when). The data can be used to predict the response of customers to a new offer or to predict customer retention/churn. Such predictions are very useful, for example, for selecting the most promising prospects for a mailing or for selecting customers in need of special attention because they have a high likelihood of leaving the company. A large set of techniques is available for this kind of "predictive modeling". Prominent techniques are neural networks (NN) and classification and regression trees (CART). Both techniques are rooted in artificial intelligence. CRM is a quickly growing area of marketing. Companies want to achieve maximum return on their often huge investments in customer databases. Therefore, further sophistication of predictive modeling techniques for future customer behavior is very important.

4.4.3 Analogical Reasoning and Case-Based Reasoning (CBR)

Analogical reasoning plays an important role in human perception and decision making. When confronted with a new problem, people seek similarities with earlier situations and use previous solutions as the starting point for dealing with the problem at hand. This is especially the case in weakly structured areas, where there is no clear set of variables that explain the relevant phenomena or define a precise objective. In marketing we have many such problems, for example in product development, sales promotions, and advertising. Goldstein (2001) found that product managers organize what they learn from analyzing scanner data into a set of stories about brands and their environments. Analogical reasoning is also the principle behind the field of case-based reasoning (CBR) in Artificial Intelligence. A CBR system comprises a set of previous cases from the domain under study and a set of search criteria for retrieving cases for situations that are similar (or analogous) to the target problem. Applications of CBR can be found in domains such as architecture, engineering, law, and medicine. By their nature, many marketing problems have a perfect fit with CBR. A recent application uses CBR as a decision support technology for designing creative sales promotion campaigns (Althuizen and Wierenga, 2010). We believe that analogical reasoning is a fruitful area for synergy between marketing and AI.

4.4.4 Role of AI in Marketing

Overall, considering the emphasis of artificial intelligence on reasoning and judgment in decision making (which are prevalent in marketing), it is surprising that the contribution of AI to marketing is so limited[3] (Wierenga, 2010). There are several (possible) reasons for this. Modern marketing management as a field emerged in the late 1950s. At that time, operations research and econometrics were already established fields while artificial intelligence as a field was in its infant stage at that time. OR and econometrics have well-defined sets of techniques and algorithms, with clear purposes and application goals. They mostly come with user-friendly computer programs that marketers can directly implement for problem solving. AI, on the other hand, comprises a heterogeneous, maybe even eclectic, set of approaches, which often take considerable effort to implement. Moreover, most marketing academics are not trained in the concepts and theories of AI. AI techniques are

[3] Here we refer to the explicit use of AI in marketing. Of course, AI principles may be imbedded in marketing-related procedures such as search algorithms for the Internet.

mostly applied to weakly structured problems and it is often difficult to measure how much better a solution is due to the use of AI, for example, a new product design or a new advertising campaign. Many marketers seem more at ease with rigorous analytics than with soft computing.

The number of publications about AI approaches in the marketing literature is limited and the same holds for the presence of marketing in the AI literature. This is regrettable, because the nature of many marketing problems makes them very suitable for AI techniques. There is a real need for decision technologies that support the solution of weakly structured marketing problems. Van Bruggen and Wierenga (2001) found that most of the existing MMSS support the marketing problem-solving mode of optimizing, but that they are often applied problems that are not appropriate for optimizing. This is important, because their study also showed that a bad fit between the marketing problem-solving mode and the decision support technology applied results in less impact of the support system. If artificial intelligence can help with decision support tools for solving less structured marketing problems, this would be very welcome.

4.5 New Types of Marketing Management Support Systems

In recent years, a new type of marketing management support systems has emerged: customer relationship management systems, or briefly CRM. Customer relationship management is an enterprise approach aiming at understanding *individual* customers and communicating with them in a way that improves customer acquisition, customer retention, customer loyalty, and customer profitability (Swift, 2001). The development of marketing management support systems based on data of individual customers marks a new era in the development of marketing.

4.5.1 Customer Relationship Management Systems

Looking at the development of marketing over time, we can say that CRM is an exponent of the third era of marketing. Marketing originated with its main focus on distribution, and the first era of marketing (1900–1960) can be characterized as *marketing as distribution.* The second marketing era (1960–2000), with its emphasis on the instruments of the marketing mix and the management of products and brands marketing, can be described as *marketing as brand management*. In this type of marketing the brand is the focus of all marketing activities and marketers are targeting the market as a whole or as groups of customers within markets (market segments). In contrast to this, the defining characteristic of the third marketing era (2000–. . .) is its focus is on the *individual customer*. Given the information about the preferences and purchase histories of individual customers, the purpose is to deal with each customer in such a way that the (long term) value of that customer is maximized. Therefore, an appropriate name for the third marketing era is *customer-centric marketing*. Information technology has made it increasingly easy to collect and retain information about individual customers. With such information a company knows precisely with whom it is dealing and it can figure out the best way of interacting with each individual customer.

4.5.1.1 The customer database

Table 4.3 presents an outline of a typical customer database, which is the heart of any CRM system. The CRM database, which is the heart of a CRM system, contains for each customer, information about *customer characteristics*, in the case of consumers usually demographics, such as gender, age, and education, and in the case of business customers variables such as industry and company size. The next item in the customer database is *interaction data*, that is information about how and when interaction occurred between the company and the customer, for example phone calls, email exchanges, complaints, sales calls, and service calls. Next, there is information about the *purchase history* of the customer: when did the customer make purchases, and how much was purchased at these occasions? Usually, a company also keeps records of the *offers and responses*, that is, specific offers made to customers and how customers responded to these offers. The last information item in the CRM system is the *profit potential*, for example the probability that the customer will respond positively to our next offer or the lifetime value of the customer (see later).

The database outlined in Table 4.3 contains data of n customers, with for each customer, a_1 attributes with data on customer characteristics, a_2 attributes on interaction history, a_3 attributes on purchase history, a_4 attributes on offers and responses and a_5 attributes on profit potential. Since the number of customers in the database can easily go up into the thousands or higher, and the number of attributes in the different categories can be very large as well, is it clear that the size of customer databases can be huge, which makes them only manageable with today's powerful computer technology.

It is clear from Table 4.3 that individual customers are the basic units of a CRM database. This is quite different from databases in the brand management era, which tended to be organized around brands, with variables such as advertising expenditure, price, sales promotions, sales, market shares, and profit per brand or product. The creation of a CRM database from existing databases can be a huge effort. For example, banks used to have different databases for each product, such as checking accounts, savings accounts, mortgages, and investments. In order to make the transition to the age of CRM, the data from these different product databases have to be brought together for each and every individual customer. Once this has been done, for a particular customer it is immediately clear what and how much business she is doing with the bank. The structure shown in Figure 6.3 can be used for consumers as well as for business-to-business (organizational) customers. As mentioned earlier, in the case of consumers, customer characteristics would refer to items such as gender, age, and education. When the customer is an organization, characteristics such as industry and size (number of employees, annual revenues) are relevant characteristics. In the latter case the CRM system should also contain information about names and functions of the contact person(s) in the organization.

4.5.1.2 CRM for two purposes

CRM systems are used by companies for two main purposes. The first is to support everyday interactions with customers. This is called *operational CRM*. For example, when a customer calls or sends an email with a complaint, the CRM system can provide instantly all the relevant

Table 4.3. Structure of a customer database.

Customer nr.	Customer Characteristics (a_1)	Interaction History (a_2)	Purchase History (a_3)	Offers and Responses (a_4)	Profit Potential (a_5)
1	....	....	....	....	....
2	....	....	....	....	....
3	....	....	....	....	....
4	....	....	....	....	....
5	....	....	....	....	....
6	....	....	....	....	....
7	....	....	....	....	....
8	....	....	....	....	....
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information about that customer, whether it is a minor or a large customer, what type of industry the customer is in (for business clients), if there is a complaint history with this customer, and the time and content of recent interactions (for example, has this customer called before with the same complaint, and how did the company respond?).

The second type of use of CRM is called *analytical CRM.* Here the CRM database is analyzed to enable firms to leverage on these data and find new marketing opportunities, for example, the need for specific products/services among certain customer groups, opportunities for cross-selling, and opportunities for event-driven marketing. Of course, for analytical CRM specialized models are needed. For a recent overview of CRM models, the reader is referred to the recent comprehensive textbook by Blattberg et al. (2008).

There are enormous opportunities for the analysis and optimization of marketing actions with the data in a CRM system. An example of a frequently employed methodology is data mining. With data mining a prediction model (e.g., a neural net, see Hruschka, 2008) is trained to learn the association between customer characteristics (for example, demographical information and purchase history) and interesting dependent variables (for example, whether or not the customer has accepted a specific offer). Once the model has been trained, it can be used to predict whether other customers (with known characteristics) will accept the offer. This technology is typically used in marketing campaigns for the selection of those customers from a database that have a high probability of accepting a particular offer. Data mining can create large savings because of a better allocation of expensive marketing resources. As Reinartz and Venkatesan (2008) demonstrate, many questions can be answered with the intelligent use of the data in CRM systems, such as: which customers should we acquire, which customers should we retain, and which customers should we grow? Related issues that have been studied recently are how many customers will be "alive" (i.e., still buying) at a certain point in time (Fader et al., 2005) and how we can predict customer "churn", i.e., the probability that a customer with a known purchase history will defect (Neslin et al., 2006). Such analyses produce actionable information: if you know which customers have a high probability of defecting, you can take selective action. Accurate CRM databases constitute a major strategic asset for a company. In the words of Glazer (1999) the customer information file (CIF) is the "key asset of a corporation" and he recommends companies to "capitalize on their chief corporate asset: information about their customers".

4.5.1.3 Customer lifetime value

When a company has a customer database at its disposal (perhaps including also potential future customers), it will typically try to attach a label to each customer expressing the monetary value of that customer to the company. This number often referred to as *customer equity* or *customer lifetime value*, which is the discounted expected stream of future profits from that customer. In order to compute the lifetime value of a customer, information is needed about the volume of sales to that customer, about margins, about the probability of retaining the customer (loyalty) and about the appropriate discount rate (Gupta and Lehmann, 2008; Reinartz and Venkatesan, 2008). The value of a customer is often used as a directive for how that customer should be treated by the employees of the company. For example, when customers have problems, typically high-value customers get service priority above low-value customers. For more information about the measurement and management of customer equity, the reader is referred to another issue in the Foundations and Trends in Marketing series (Villanueva and Hanssens, 2007).

Customer Relationship Management (CRM) has been called the "new mantra of marketing" (Winer, 2001) and recently, companies have been installing CRM systems at a high rate. Many companies have CRM systems in place now. The advent of CRM systems implies a quantum leap in the number of marketing management support systems in companies. Interestingly, the companies that are at the forefront of implementing CRM systems are not the same companies that were dominant in the development of MMSS for brand management. The CRM movement is particularly strong in industries such as financial services (e.g., banks and insurance companies), telecommunications, utilities, entertainment, recreation, and travel. In the consumer-packaged goods industry, where the first developments in marketing management support systems took place, CRM has less impact.

4.5.2 Marketing Dashboards[4]

Marketing data has become available in ever larger quantities and with ever richer varieties. The fragmentation of media, the emergence of multiple channels, the proliferation of product lines and services, and the registration of data at the level of the individual customer have contributed to this data abundance. How can marketing decision makers cope with the resulting complexity? Marketing dashboards are an increasingly popular answer among companies. A marketing dashboard (MDB) brings the key metrics and indicators, needed for effectively managing the marketing function in a company, together in one single visual display. In the same way that the dashboard in a car gives the driver crucial information for navigating the car (how far have you traveled? how much fuel is left? where do you want to get today?), a marketing dashboard provides information that is needed for successfully navigating a company marketing-wise.

A dashboard can be defined as: "a relatively small collection of interconnected key performance metrics and underlying performance drivers that reflect both short- and long-term interests to be viewed in common through the organization" (Pauwels et al., 2009). Figure 4.3 presents an example of a type of dashboards that a marketer can use. This example executive dashboard can be used for tracking high-level marketing performance metrics in one simple high-level executive dashboard. The graphical display allows for views of multiple levels of performance. This example illustrates geographic and product group comparisons. It could also include individual products, product groups, or geographies (see http://appiananalytics.com/analytics/dashboards-gallery.htm for other examples).

Two observations about the definition of marketing dashboards, given above, can be made. First, a marketing dashboard contains a

[4] This section is based on Pauwels, K., T. Ambler, B.H. Clark, P. Lapointe, D. Reibstein, B. Skiera, B. Wierenga, and T. Wiesel (2009), "Dashboard as a service: Why, what, how, and what research is needed," *Journal of Service Research* 12(2), 175–189.

Fig. 4.3 Example screen of a marketing dashboard.

small number of key metrics. This number has to be small because of the limited capability of the human mind in dealing with different items at the same time (Miller, 1956). It is important that a manager can mentally "grasp" the situation in one glance. Second, a dashboard has the purpose of *integration*, in several respects. The dashboard integrates (i) *data* (from different sources inside and outside the company); (ii) *processes* (from marketing expenditures to financial performance); and *viewpoints* (from different marketing executives, but also executives from other departments, e.g., finance). Related to the last item, a dashboard should help to establish the culture of the organization (by looking at the same criteria), consensus building, and organizational learning. This is expressed by the term "in common" in the definition.

4.5.2.1 The metrics in the dashboard

Since their number is limited, the decision about which metrics go into the dashboard is crucial. Most often a *general approach* is followed,

Table 4.4. General metrics in a marketing dashboard (adapted from Ambler, 2003).

P&L Metrics	Brand Metrics
— Sales	— Awareness
— Profit	— Market Share
— Marketing Expenditures	— Penetration
	— Attitudes and Loyalty
	— Availability

which keeps the number down to a few that can be applied in virtually all settings. A list of such metrics, adapted from Ambler (2003), is given in Table 4.4.

The metrics in Table 4.4 are geared toward a brand management orientation (second era of marketing). In a more CRM-oriented context Wiesel et al. (2008) propose the following five key performance metrics:

- number of customers
- customer cash flow
- retention rate
- acquisition expenditures
- retention expenditures.

In a *tailored approach* the metrics are chosen and defined for the specific situation of a particular organization. This offers the advantage of generating a discussion throughout the organization of what is important for the business, and hopefully arriving at a consensus. It can also be very demanding, take a lot of time, and result in a compromise of too many metrics.

Ideally, a dashboard should not be restricted to just delivering numbers for the chosen metrics, but should also contain information about the drivers of these metrics, and about the relationships between dashboard items. This means not only status reporting, but also response reporting (Little, 1979b) and requires analytical capabilities. The metrics in an MDB should make it possible to monitor how marketing efforts (perhaps through a number of intermediary steps) ultimately result in bottom-line results for the company. Using response models Brand Metrics can be linked to P&L Metrics.

The highest level of an MDB is typically meant for the target group of senior managers. These include non-marketing executives, such as the CFO and the controller. (In this way a marketing dashboard also helps to make marketing more accountable.) Typically, an MDB has drill-down capabilities, which makes it possible to look in more detail at specific products, specific countries, and specific groups of customers or even individual customers. These features will more frequently be used by middle-level managers for their specific responsibilities.

A marketing dashboard is a marketing management support system. Evidently, it has features of marketing information systems (MKIS) in that it summarizes the past, but with an emphasis on *evaluation* by providing *key performance* indicators. Marketing dashboards that are also able to analyze the drivers of performance and to carry out sensitivity analyses with respect to decision alternatives have properties of marketing decision support systems (MDSS). In a sense CRM systems and marketing dashboards are opposites. CRM systems capitalize on the data richness of the contemporaneous marketing environment and enable marketing at the very disaggregate level of the individual customer. Marketing dashboards summarize all available information in a few key metrics that a (human) manager can cope with when dealing with the broader picture of the overall marketing strategy of the company.

4.6 The Match Between Marketing Problem-Solving Modes and Marketing Management Support Systems

The ORAC model describes how a marketer solves various kinds of marketing problems, and represents the *demand side* of marketing management support. The different types of marketing decision support systems, discussed in Section 2, represent the *supply side* of marketing management support systems. Different types of MMSS are suitable for different purposes. For the successful application of MMSS a good match is needed between the marketing problem-solving mode (the demand side) and the type of MMSS. Table 4.5 shows the relationship between marketing problem-solving modes and the most appropriate types of MMSS.

Table 4.5. The match between marketing problem-solving modes and marketing management support systems.

Marketing problem-solving mode	Most suitable marketing management support system(s)
Optimizing	Marketing Models CRM models Marketing Expert Systems
Reasoning	Marketing Information Systems Marketing Dashboards Marketing Decision Support Systems Marketing Neural Nets Marketing Knowledge-Based Systems
Analogizing	Marketing Case-Based Reasoning Systems Marketing Neural Nets
Creating	Marketing Creativity Support Systems

4.6.1 Optimizing Support

In the case of optimizing, a best solution exists and the marketing management support system should ensure that this solution is found. The first type of marketing management support systems that became available to match the design requirements of the optimizing mode is marketing models. Marketing models provide a mathematical representation of the marketing problem and can be used, in combination with an optimization algorithm, to find the objectively best solution for the values of the marketing instruments. Given the input data (e.g., objectives, resources) the algorithm produces a solution like the best media plan, the optimal shelf-space allocation in a supermarket, the optimal number of seed emails in a viral marketing campaign, or the optimal sales call schedule. The solution of the problem can be delegated to a lower skilled employee who is able to run the optimization procedure, but does not need to have a lot of marketing expertise. As we have seen before, full automation of marketing decisions is still rare, but is becoming more customary. The area of customer relationship management (CRM) is an example of a field where a high degree of marketing automation is possible, for example, when a computer decides whether a particular customer gets a specific offer, based on the purchase history of that customer.

Whereas marketing models provide the best *quantitative* solution, marketing expert systems aim at providing the best solution if the problem is described in terms of *qualitative* relationships between the variables. Under the optimizing mode, a marketing model might be used to determine the advertising budget and, subsequently, a marketing expert system might be used to find out how the copy and the execution of the advertisements should look like. Again, since the expertise is in the system, within the predetermined solution space a relatively low skilled person can, in principle, find the solution.

4.6.2 Reasoning Support

The mental model of the decision maker is the core of the reasoning mode. The decision is the result of a process in the decision maker's mind. Therefore, in the reasoning mode, the object of support for the decision maker should not be a particular outcome (a precise recommendation on what to do) but the marketing manager's *decision making process.* Under the reasoning mode, a marketing management support system should provide information about what is going on in the market and actively draw a manager's attention to significant events.

Marketing management support systems can support the reasoning mode in two different ways:

(a) by supporting the formation and maintenance of managers' mental models; and
(b) by reasoning with these mental models.

For (a), information is needed about what happens in the market — that is, actual facts and data (answering the "what" question[5]). This is the main function of marketing information systems and marketing dashboards. Because of its model base, a marketing decision support system can also help the decision maker to obtain an understanding of the mechanisms in a market by obtaining a systematic insight into the relationships between key marketing variables, such as between

[5] The distinction between what, why, what-if, and what should questions, is introduced in the Introduction and will be elaborated upon in the following chapter.

advertising expenditures and brand awareness and between advertising expenditures and sales. Kayande et al. (2009) present a study of how MMSS help to adapt the mental models that decision makers have about the market. By means of simulation (i.e., answering "what-if" questions), a marketer can use a marketing decision support system to explore the consequences of alternative marketing strategies. Marketing neural nets can also help to explore what is going on in a market. A marketing neural net can discover patterns in the interdependencies between marketing variables — for example, capture the characteristics that distinguish successful from unsuccessful new products.

For (b) a decision maker's mental model is coded in a computer and subsequently the computer can reason with this model. A marketing knowledge-based system is particularly suited for this purpose. Systems can be built for monitoring and diagnosing market events and suggesting appropriate actions in the same way as the manager would do. An early example of such a system is CoverStory (Schmitz et al., 1990; Schmitz, 1994). CoverStory produces short reports and graphs about the most important events in a market, based on the analysis of scanning data. Such marketing knowledge-based systems can search very large amounts of data for significant marketing events and act as an efficient electronic assistant of a marketing decision maker. In the era of the "marketing information revolution" such systems are becoming indispensable because of the sheer size of databases.

4.6.3 Analogizing Support

In the analogizing mode the decision maker uses solutions from earlier, similar decision situations to develop a decision for a current problem. Therefore, in the analogizing mode the process of finding suitable cases and adapting them for the current problem situation is the primary object of support. Marketing case-based reasoning systems are the type of marketing management support systems that match the requirements of the analogizing mode. The development of case-based reasoning technology was inspired by the desire to support the analogy-seeking behavior of decision makers. Case-based reasoning systems consist of (large) sets of cases stored in a computer, with efficient indexing systems for finding the cases that are similar to a problem situation at hand, and with facilities to transform or adapt earlier solutions to the current. For example, a product manager developing a sales promotion for a brand can be inspired by a campaign, present in the case base that has been previously successful for a similar product in a different market. The strength of a computer-based case-based reasoning system is that it augments a decision maker's memory by providing access to a large collection of relevant cases. Human decision makers, on the other hand, are fairly good at adapting these cases to the situation at hand (Dutta et al., 1997). Ultimately, in the analogizing mode, as the number of cases in the case base grows larger, some form of generalization takes place (learning from experience). For that purpose, marketing neural nets may be used to search for patterns in the cases of the case base.

4.6.4 Creating Support

In the creating mode the marketing decision maker searches for concepts, solutions, or ideas that are novel, often in response to a situation that has not occurred before. Here a marketing management support system should support the creative process and should fulfill a stimulating role — that is, generate cues and ideas that trigger the user. Creativity consists to a large extent of making connections and associations between (remote) concepts. This can be facilitated by a marketing management support system. There is an emerging class of creativity support systems that match well with the demand for creativity support in marketing (Garfield, 2008).

5

How Do Marketing Management Support Systems Support Marketers?

As we have argued before, it is rarely the case that a marketing management support system completely takes over the job of a marketing decision maker. Unlike relatively more structured jobs in accounting or control, most marketing tasks cannot be easily left to a computer. A much more common situation is that the marketing decision maker interacts with and is supported by the MMSS (see Figure 1.1). It is no coincidence that highly educated and skilled personnel tend to be recruited for marketing management jobs, even for the marketing of relatively simple products like margarine or beer.

Marketers often work in highly competitive and constantly changing situations. This means that the relevant variables and criteria also constantly change and that marketers constantly need to judge what kind of decisions have to be made and how the characteristics of the decision situation affect what the optimal decision or action in a certain case is. Instead of replacing the marketing manager, the role of a marketing management support system should be that of a sparring partner, which enhances the manager's effectiveness as a decision maker. In this section we discuss how a marketing management support system can help a marketing manager to perform better.

5.1 Marketers' Cognitive Limitations in Data Processing

The enormous quantities of data offer opportunities for a systematic analysis and for the support of marketing policies. Prior to the availability of all of this data, marketing was usually considered an art where the creativity of the marketer was an especially important asset (Ing and Mitchell, 1994). Although creativity remains a key asset of marketers, decision makers now can and should benefit from the availability of more and better data by incorporating the information derived from this data into their decision making processes (Blattberg and Hoch, 1990).

In processing information, decision makers may, however, show cognitive limitations. These limitations can lead to biased decision making processes in decision environments that have become complex because of data and information abundance. Biased decision making processes will lead to non-optimal decisions, and marketers will thus not fully benefit from the opportunities that the marketing information revolution offers. Marketing management support systems should help to circumvent these biases in human decision making.

Marketing management support systems can be effective both by reinforcing the strengths of marketers (e.g., creativity, domain knowledge, flexibility, and so on) and by compensating for their weaknesses. We distinguish two mechanisms by which MMSS can be effective: (1) by means of organizing data, which reduces the amount of perceived complexity, and by transforming marketing data into marketing information, insights, and knowledge; and (2) by means of reducing the biasing effects of a decision environment that has become (too) complex because of data abundance.

5.2 Combining Managerial Judgment and Marketing Management Support Systems

While the sheer 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). The marketing manager of today, living in the time of the "marketing data revolution," is equipped with the same cognitive abilities as colleagues from the "prehistoric" marketing era before computers were available. Marketing management support systems should come to the rescue. What is (or can be) especially successful is the combination of manager and system (Blattberg and Hoch, 1990).

An important function of an MMSS is its ability to remove biases from decision making processes. Several studies have demonstrated these effects. Hoch and Schkade (1996) found that in forecasting tasks, decision makers often use their experience from earlier situations. This strategy performs reasonably well in highly predictable environments but is less effective when the environment is less predictable. Their experiment showed that a marketing decision support system in the form of a simple linear model can prevent or overcome these biases. In a laboratory experiment using the MARKSTRAT simulation, Van Bruggen et al. (1998) found that in a complex decision environment the use of an MDSS makes decision makers less susceptible to applying the anchoring and adjustment heuristic for making marketing-mix decisions.

Unlike human experts, models are strong in that they are not subject to decision biases of perception and evaluation; experts often suffer from overconfidence and may be influenced by politics, whereas models take base rates into account and are immune to social pressures for consensus; experts can get tired, bored, and emotional, whereas models do not; and experts do not consistently integrate evidence from one occasion to another, whereas models weight this evidence optimally (Blattberg and Hoch, 1990; Hoch, 1994). The strengths of models also extend to the use of marketing expert systems, marketing knowledge-based systems, marketing neural networks, and marketing decision support systems. All of these systems are computer-based, derive information from data, and develop suggestions for decisions based on a *systematic analysis* of data. Such a systematic analysis will not be affected by decision biases, overconfidence, fatigue, or inconsistencies.

The ever-growing quantity of available data is a fact of life. Competitive advantage will, therefore, not so much derive from just having lots of these data, but from having the right marketing management support systems in place to get the most out of it.

5.3 How Should a Marketing Management Support System Support a Marketer?

Should a marketing management support system reinforce the strengths of a decision maker or should it compensate for the marketer's limitations? On the one hand matching marketing management support systems with the demand (user) side implies that decision makers get the type of support that fit with their competencies. This implies that, for example, analytically oriented decision makers get sophisticated marketing models. Kayande et al. (2009) propose that decision makers will be more likely to accept an MMSS when their mental models of the decision environment are aligned with the decision model embedded in the MMSS. On the other hand it seems natural to use marketing management support systems to compensate for the limitations of decision makers. For example, Van Bruggen et al. (1998) found that low-analytical decision makers benefit most from an analytical marketing management support system. Althuizen and Wierenga (2010) found that creativity support systems are most effective for decision makers with low-to-moderate innate creative ability. Compensating for limitations in human cognitive capabilities, such as described here, is a widely used decision support approach. Suppose that an MMSS needs to support the reasoning mode. In the case of reasoning, the marketer has a mental model that may consist of cause-and-effect relationships. In principle this model allows the marketer to perform what-if simulations. However, because of human decision makers' cognitive limitations (e.g., Simon, 1979; Hogarth and Makridakis, 1981) a decision maker will only be able to consider a limited number of alternative solutions. A system offering "what-if" capabilities can extend the decision maker's mental capacity in using the reasoning mode and we thus expect this to improve the decision maker's performance. In this sense a system that compensates for the weaknesses of a human decision maker can be effective.

Sometimes decision makers seem to be aware of their own limitations. In a study of De Waele (1978), individuals appeared to prefer the decision aid that complemented their weakest style instead of supporting their strongest. Low-analytical decision makers preferred analytical aids. In other situations decision makers were found to be less enlightened. Designers of decision support systems have paid little attention to the psychology of the decision maker (Hoch and Schkade, 1996) despite the importance of taking the personality of the decision maker into account. Maybe the issue of reinforcing existing strengths or compensate for weaknesses is not an either/or question. Marketing management support systems can fulfill both roles. MMSS should be designed not only to take advantage of the distinctive competencies of decision makers, but also to compensate for their inherent weaknesses (Hoch and Schkade, 1996). As the designers of MMSS become more involved in complex, unstructured problems, they will need to develop a clearer understanding of how managers go about making these complex strategic decisions.

In the combination of the MMSS and the marketing decision maker, managers need to be aware of the risk of allowing the MMSS to guide their activities, instead of the demands of the decision situation at hand (Glazer et al., 1992). Marketing management support systems should not replace marketers and in the process lose their strengths in judgment and intuition, but rather extend the human cognitive capacity.

5.4 The Effectiveness of Marketing Management Support Systems

A priori, we can thus expect decision models to have a positive effect on decision outcomes for several reasons. Decision makers have cognitive limitations in acquiring and processing information (Tversky and Kahneman, 1974; Hogarth and Makridakis, 1981; Bazerman, 1998). When confronted with large amounts of information in short-time frames, they may use heuristic approaches to solve problems, which trigger various cognitive biases that could diminish decision quality. An MMSS can potentially be a debiasing tool to reduce several types of biases (Arnott, 2002). In making marketing decisions, MMSS can help managers to cope with large amounts of information and integrate that information in a consistent way (Dawes, 1979). In particular, an MMSS may help managers choose good strategies by consistently weighting the available options according to specified criteria, whereas humans tend to alter the weights they assign to different variables by using heuristics. Thus, good decision support technologies should be designed to provide decision makers with capabilities needed to extend their bounds of rationality (Todd and Benbasat, 1999).

The extent to which an MMSS improves the quality of decision making processes and decision outcomes will depend on what the MMSS has been designed to do (Silver, 1990) and on how well it performs (Van Bruggen et al., 1996). Since users often adopt a "cost-benefit" approach, by which they assess the tradeoffs between decision quality and the effort they need to invest in the decision making process (Payne et al., 1993) the actual decision will result from a compromise between their desire to make a good decision and their desire to minimize effort. Decision makers tend to favor effort reduction (Payne et al., 1993) and only focus on enhancing decision quality if they expect that incremental effort will lead to a large gain (Todd and Benbasat, 1999). If an MMSS plays a role in the decision making, it can alter this quality-effort tradeoff. However, the mere availability of an MMSS will not improve decision quality. An MMSS can reduce cognitive effort (simplify the decision process with little or no improvement in outcome) or enrich the decision process, perhaps even leading to more effort and better results. Thus, reducing cognitive effort will not necessarily improve decision quality; decision makers must deploy the "saved effort" to explore more decision alternatives or to explore decision alternatives in greater depth to realize improved outcomes. This will happen *if* the user is motivated by the MMSS to deploy more cognitive effort to the task (Moore and Chang, 1983). For this to happen it is important that the decision makers perceive the MMSS to be useful (Davis, 1989) and to fit with their decision making tasks.

The *Fit Appropriation Model (FAM)* (Dennis et al., 2001) proposes that the effects of (group) DSSs are affected by two factors. The first is the *fit* between the task and the DSS, i.e., the task-technology fit. The second is the *appropriation support* the group members receive in the form of training, facilitation, routinization, or software restrictions to help them incorporate the system effectively into their decision making process. FAM proposes that task-technology fit is a necessary, but not sufficient condition, to improve decision performance. Without proper appropriation support, performance is less likely to improve much even when task-technology fit exists. That is, the effect of task-technology fit on performance will be moderated by appropriation. Appropriation itself, in turn, is affected by the fit (a good fit is more likely to lead to faithful appropriation). However, empirical results show that even without appropriation support, performance may still be influenced positively, whereas the subjective evaluations (e.g., satisfaction with the decision) may not be (positively) influenced (Dennis et al., 2001). Hence, the FAM model suggests that MMSS can be expected to have a positive effect on objective decision outcomes if they show a sufficiently high level of task-technology fit. Given decision makers' tendency to choose effort reduction, and the fact that merely following the recommendation of a high-quality MMSS offers both low effort and high decision quality, we can expect high-quality MMSS to improve objective decision quality (incremental return/profit).

5.5 Empirical Studies on the Effectiveness of Marketing Management Support Systems

Since the early 1970s, much empirical research has been conducted studying *whether* the use of Marketing Management Support Systems improves the quality of decision making (see Table 5.1 for a summary of these studies). Most of these studies were experimental either in a field setting (e.g., Fudge and Lodish, 1977) or in a laboratory environment (e.g., Chakravarti et al., 1979). Most of the DSS were used to support resource allocation decisions, while the DSS in the study of Hoch and Schkade (1996) supported a forecasting task and the DSS in the studies of Van Bruggen et al. (1996, 1998) supported decisions about marketing-mix variables.

Analyzing these studies leads to a number of observations. First, with the exception of the study of Chakravarti et al. (1979), all other studies show that the use of MMSS has a positive impact on the quality of marketing decision making leading to better organizational performance. The positive impact of these models/systems is probably caused by their high quality and the fact that most of these systems were developed for environments that were relatively well-controlled and where it

Table 5.1. Major studies on the impact of MMSS.

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	Key Results/Comments
Fudge and Lodish (1977)	Evaluate the effectiveness of a DSS (Decision Calculus model)	Allocation of sales effort at Air cargo services of United Airlines	Field	Availability of the CALLPLAN DSS, including training	Objective: Sales	After six months, salespeople who used a DSS had significantly higher sales (+8% on average). DSS users viewed the system as productive.
Chakravarti et al. (1979)	Evaluate effectiveness of a DSS (Decision Calculus model)	Allocation of ad budget over several periods (includes carry-over effects)	Lab	Availability of the ADBUDG DSS	Objective: Profits; Accuracy of parameter estimates of underlying model	Subjects made better decisions before being exposed to the DSS. System use did not lead to improved estimates of parameters (but the simulated dynamic environment seems to be overly complex).
McIntyre (1982)	Evaluate effectiveness of a DSS (Decision Calculus model)	Allocation of ad budget over several periods (no carry-over effects); sales prediction	Lab	Availability of the CALLPLAN DSS; Task characteristics (size of the problem, noise-to-signal ratio in market); Characteristics of decision makers	Objective: Profits; Accuracy in predicting sales; Stability Subjective: Confidence in decision	DSS users achieved higher profit levels with less volatility, but they did not do better in predicting sales levels. There was no difference in the perceptions between model users and non-users that the allocations result in profits near to optimal profits. However, decision makers felt more confident when using the DSS.

(*Continued*)

Table 5.1. (*Continued*)

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	Key Results/Comments
Lodish et al. (1988)	Assess effectiveness of a DSS (Decision Calculus model)	Allocation and sizing of sales force (Syntex Laboratories Inc.)	Case study	Actual implementation of DSS (CALLPLAN) in a company.	Objective: Sales/Gross Margin	DSS helped Syntex decide to significantly increase its sales force size and to change its effort allocation to products and market segments. This decision resulted in a documented continuing \$25 million–8%–yearly sales increase.
Gensch et al. (1990)	Assess effectiveness of a DSS (multi-attribute disaggregate choice model) for segmentation and targeting	Allocation of marketing effort based on model predictions with respect to choice among suppliers of ABB Electric Inc.	Case study	Actual implementation of DSS (multi-attribute disaggregate choice model) in a company.	Objective: Sales	ABB used the model to segment and target customers. After a year of implementation, total transformer sales for the industry were down 15%. In contrast, ABB sales in the two districts using the DSS increased (18% and 12%), whereas its sales in the territory not using the DSS methods were down 10%. The management at ABB Electric felt that the DSS was a competitive advantage that led them to grow market share from 4% to over 40% over a fifteen-year period along with increased profitability in a highly competitive market.

(*Continued*)

Table 5.1. (*Continued*)

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	Key Results/Comments
Hoch and Schkade (1996)	Evaluate DSS effectiveness in combination with experience (pattern matching efforts)	Forecasting of credit ratings	Lab	Availability of DSS (linear model); Availability of database support (pattern matching support); High/low predictability of environment (credit rating)	Objective: Accuracy of forecasting performance	In the high predictability environment, aided users did better, but not significantly better than unaided users. In the low predictability environment, users with database support (pattern matching) did significantly worse than the? model only or unaided. Users with DSS and database support did best.
Van Bruggen et al. (1996, 1998)	Assess the impact of differences in DSS quality	Marketing-mix decisions in the MARK-STRAT simulation environment.	Lab	Availability of DSS (what-if model for sales and market share predictions)	Objective: Profit De-anchoring	DSS users achieved higher profits than non-users. Although users of high-quality DSS outperformed users of lower quality DSS, there was no significant difference in perceived usefulness or decision confidence.

(*Continued*)

Table 5.1. (*Continued*)

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	Key Results/Comments
				High/low DSS quality (i.e., the prediction precision) High/low time-pressure	Subjective: Perceived usefulness, Decision confidence	DSS users were less susceptible to applying the anchoring and adjustment heuristic and, therefore, showed more variation in their decisions in a dynamic environment. Low-analytic subjects and subjects operating under low time pressure benefited most from a DSS.
Lilien et al. (2004)	Assess how DSS influence decisions	Two different resource allocation tasks: Sales force allocation (see Lodish et al., 1988) and target segment selection (see Gensch et al., 1990)	Lab	Availability of DSS Task order	Objective: Incremental return (profit or sales) Extent of de-anchoring Expert ratings Subjective: Complexity, Cognitive effort, Satisfaction, Discussion Quality, Learning, etc.	DSS use improves objective decision outcomes for both DSS models. However, DSS users often do not report better perceptions of outcomes. Expert evaluators had difficulty detecting objective decision quality. Effects of DSS on both process and outcomes may be context and DSS-design specific, with DSS that provide specific feedback having stronger effects both on the process and on the outcomes.

(*Continued*)

Table 5.1. (*Continued*)

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	Key Results/Comments
Kayande et al. (2009)	How incorporating feedback mechanisms in a DSS affects DSS evaluations	Identify the most attractive donors from a database of past donors for solicitation in a direct marketing campaign.	Lab	Upside Potential Feedback Corrective Feedback	DSS Evaluation Deep Learning Effort Guidance	Dual-feedback DSS, which incorporates feedback both about upside potential (i.e., how much more can be gained by internalizing the DSS model) and feedback on corrective actions (i.e., guidance on how the manager's mental model should be corrected), would induce more effort from decision makers as well as offer appropriate decision guidance. This combination of effort and guidance then produces significant mental model updating, while single feedback DSS produce little or no updating. Mental model updating, in turn, leads to better subjective DSS evaluations than when little or no mental model updating occurs. Results show that DSS evaluations only improve after significant mental model updating, which occurs when the DSS incorporates both upside potential and corrective feedback.

Source: Lilien et al. (2001).

was possible to realize a relatively good match between the system and the decision problem. Second, because of the nature of their design in most of these studies, all participants used the systems that were available because this was part of their (experimental) task. However, in practice, getting decision makers to *use* these systems is often a problem in itself. If systems are not used, they cannot have impact. Third, most studies only looked at the effects of system use on "objective" organizational variables like sales and profit. However, some studies also investigated the subjective evaluations of system value and impact by the users by measuring variables such as decision confidence and decision satisfaction. It is remarkable that the subjective evaluations of the decisions made when using decision models are not strongly related to the objective results of model-based decision making (Lilien et al., 2004). Decision makers seem to have difficulties in recognizing the value of MMSS, or are at least uncertain, about the value these systems add to the quality of decision making. This hampers the adoption and use of these systems and, consequently, their impact on the quality of decision making. We discuss possible ways for avoiding this later in this section.

From the studies summarized in Table 5.1 we conclude that: (i) if they are used MMSS generally lead to better decisions; (ii) MMSS use does not happen automatically; and (iii) that decision makers have difficulties in recognizing the positive effects of MMSS on the quality of their decisions. So, MMSS do have *potential* impact, but the critical issue is how to realize this impact in practice. This leads to the topic of the drivers of the impact of MMSS we discuss next.

6

Implementing Marketing Management Support Systems

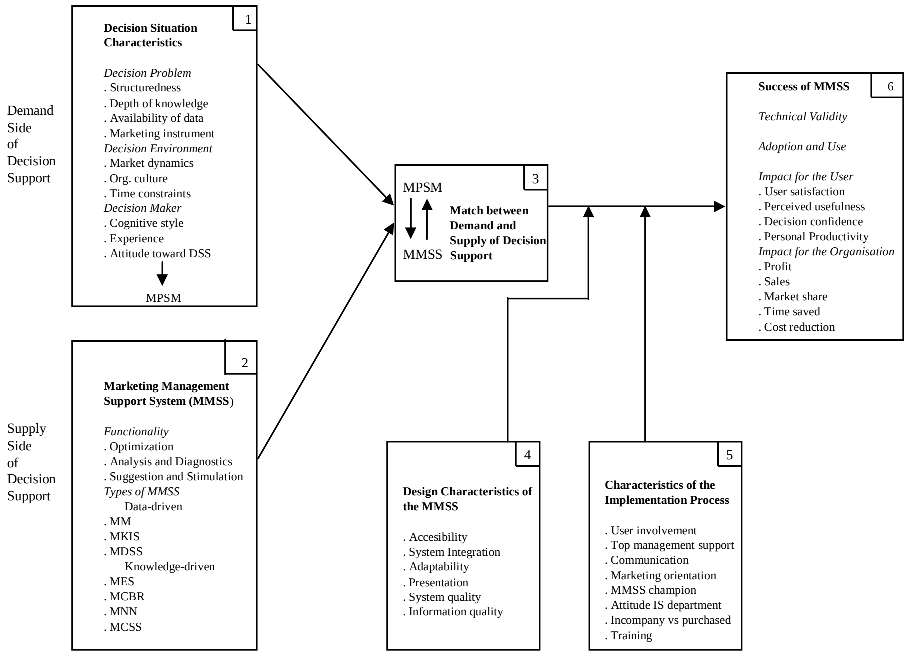
For marketers it probably does not come as a surprise that the supply of Marketing Management Support Systems does not automatically generate demand (i.e., by marketing decision makers wanting to use these systems). Over the years very sophisticated MMSS have been developed. However, these systems were not immediately used. Marketers are just like other people with their resistance to change and to new ways of doing things. Carlsson and Turban (2002) note that the key issues with decision support systems (DSS) are "people problems". "People (i) have cognitive constraints in adopting intelligent systems; (ii) do not understand the support they get and disregard it in favor of past experiences; (iii) cannot really handle large amounts of information and knowledge; (iv) are frustrated by theories they do not really understand; and (v) believe they get more support by talking to other people (p. 106). Of course, it is not fair to blame only the marketing decision makers for not using MMSS. In many cases, the systems may just not have been good enough, user unfriendly, or their advantages were not sufficiently clear to the manager.

Given the state of affairs with respect to the actual use of MMSS in companies, it is important to develop more insight into the role of "people issues" and, at a more general level, in the factors that can block (or stimulate, for that matter) the adoption and use of marketing management support tools. Systematical research (cross-section studies, field studies, lab experiments, field experiments) on these issues has been done. The knowledge acquired can be found in the Marketing Management Support Systems literature. "Marketing Management Support Systems" does not just refer to a collection of decision support systems and technologies, but also to a substantive field with an emerging body-of-knowledge about the factors and conditions that affect the adoption, use, and impact of marketing decision support tools in organizations. We present the most recent insights into this section. Earlier reviews can be found in books such as Wierenga and Van Bruggen (2000) and Lilien and Rangaswamy (2004), and in Special Issues of academic journals such as *Marketing Science* (Vol. 18, No. 3, 1999) and *Interfaces* (Vol. 31, No. 3, 2001).

6.1 What Drives the Impact of Marketing Management Support Systems?

Because of the high (technical) quality of available MMSS and the evidence that if marketers use these systems they actually do make better decisions, it is critical to make organizations adopt MMSS and decision makers within these organizations to use these systems. In this section we describe the drivers of the use and impact of MMSS.

Wierenga et al. (1999) describe an integrative framework of the factors that determine the success of a marketing management support system (see Figure 6.1). In this framework the match between the characteristics and of the decision situation (i.e., the demand side of decision support) and the characteristics of the marketing management support system (the supply side of marketing management support) determines the potential success of the system. Various success measures are distinguished. Technical validity refers to the statistical properties and quality of the system. Adoption and use refers to the extent that an organization adopts the system and users within the organization actually use it. Next, a distinction is made between MMSS impact for the individual user (e.g., personal productivity and user satisfaction) and



DSS = Decision Support System; MPSM = Marketing Problem-Solving Mode; MMSS = Marketing Management Support System; MM = Marketing Model; MKIS = Marketing Information System; MDSS = Marketing Decision Support System; MES = Marketing Expert System; MCBR = Marketing Case Based Reasoning System; MNN = Marketing Neural Network; MCSS = Marketing Creativity Support System.

Fig. 6.1 Integrative framework of the factors that determine the success of a marketing management support system (Wierenga et al., 1999).

MMSS impact for the organization (e.g., its sales and profitability). The extent to which the match between the demand side and the supply side of marketing management support will be realized depends on the characteristics of the MMSS design (e.g., its user friendliness and ease of use) and the way it is implemented (e.g., training and support).

In the current section we advance the work of Wierenga et al. (1999) by acknowledging the interdependencies between the various MMSS "Impact" variables and by taking a dynamic perspective. In Figure 6.2 we describe the overall structure of our model, which describes the drivers of MMSS Impact. In order to have impact an MMSS needs to be used and for that to happen it needs to be adopted

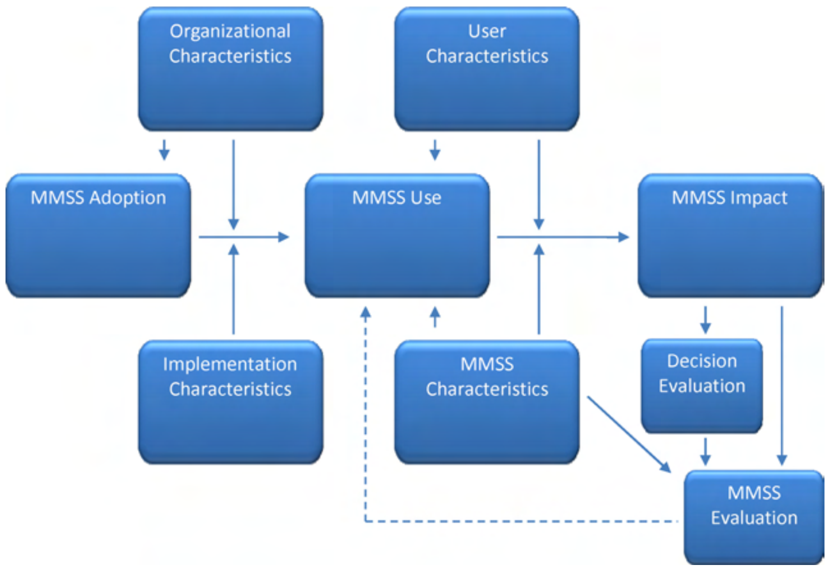


Fig. 6.2 Model that describes the drivers of MMSS impact.

by the organization. Organizational Characteristics will affect MMSS Adoption and moderate the relationship between MMSS Adoption and MMSS Use. Implementation Characteristics will also moderate the relationship between MMSS Adoption and MMSS Use. User Characteristics and MMSS Characteristics will affect MMSS Use and moderate the relationship between MMSS Use and MMSS Impact. The Impact of the MMSS will affect the Evaluations of these Decisions made using the MMSS and it will also affect the Evaluation of the MMSS. The Evaluation of the MMSS will in turn affect the MMSS Use in future decision making processes.

We will now more extensively discuss the various parts of the model in Figure 6.2. We start with the MMSS Impact construct. The Information Systems (IS) research literature has paid extensive attention to the impact of information systems and decision support systems in general. The concept of Information System Success is widely accepted throughout IS research as the principal criterion for evaluating information systems (Rai et al., 2002). Rai et al. (2002) state that a problem lies in the ambiguity of the construct and the multiplicity of IS constructs pervading the research. Researchers have been using various variables to measure the impact or success of systems. Based on a large review of multiple empirical studies, DeLone and McLean (1992) conclude that IS/DSS success is a multidimensional construct and that it should be measured as such. This is highly similar to the approach taken in Wierenga et al. (1999). DeLone and McLean propose a temporal and causal ordering between six IS/DSS success variables. System Quality and Information Quality singularly and jointly affect both System Use and User Satisfaction. Additionally, the amount of System Use affects the degree of User Satisfaction as well as the reverse being true. System Use and User Satisfaction are direct antecedents of Individual Impact and this Individual Impact should eventually have Organizational Impact. Even though alternative specifications (i.e., Seddon, 1997) of IS success models have been suggested, the DeLone and McLean model serves well as the starting point for dealing with the issue of the impact of Marketing Management Support Systems. In the impact measurement model that we develop here, we see Organizational Impact as the key dependent variable which the MMSS aims at maximizing. In our view, the other variables (DeLone and McLean, 1992) mention are antecedents of this Organizational Impact. We will elaborate on this below.

The main goal of marketing management support systems is to improve the quality of marketing management and marketing decision making within organizations. This will improve the organization's performance in the market. *Market outcomes* represent the organization's performance in the marketplace (George et al., 2007). This means making the right decisions about whether or not to introduce a new product (and when and in which market), about whether or not to introduce a sales promotion, and about how much the advertising budget or price level should be changed. Marketing performance is essentially multidimensional and a firm needs at least as many metrics as it has goals, of which short-term survival and long-term growth are the most common (Ambler and Roberts, 2006). Organizations have goals with respect to variables like their profitability, sales, brand awareness, etc. The metric that is most appropriate to evaluate the impact of a specific MMSS depends on the goal of that system. The metric can be relatively specific and uni-dimensional in the case of a specific support system. For example, the impact of a system that supports decision making on advertising decisions may be measured by the extent to which its use leads to advertising decisions that increase brand awareness or brand image. However, for systems that support a broader range of marketing activities and decisions, more general measures like effects on sales, market shares, and profitability can be employed. With the tendency in marketing to target activities at individuals, marketing metrics measured at the individual customer level, such as customer share, become more relevant.

Next to affecting the marketer's performance in the marketplace, it is highly likely that MMSS affect the way decisions are being made, that is they affect the *decision process*. These can be decision processes of the *individual* marketer or of a decision making *group*. If the MMSS is used to improve the quality of decision making, it leads to a more extensive decision process in which more decision alternatives are being explored and where the outcomes of these alternative are more thoroughly analyzed. This usually also has an effect on the market outcomes of using the MMSS. However, sometimes marketers use the MMSS especially to become more efficient in their decision making process, which is to spend less time on the process. If this is the case, the impact of the system on market outcomes (at the organizational level) may be limited. Research by Payne et al. (1993), mentioned earlier, shows that in making decisions, decision makers constantly tradeoff making better, more accurate decisions versus putting less cognitive effort into the decision making process. Research by Todd and Benbasat (1999) has shown that decision makers often use decision support tools to reduce the amount of cognitive effort they have to spend in the decision making process rather than optimizing the quality of the decisions. This means that tools are thus used for purposes which are different from those they were designed for, which was to improve market outcomes.

A reason for decision makers to use MMSS especially for improving efficiency rather than for increasing decision quality, may be that the effort they put into the decision making process is immediately observable by them. The effects of using MMSS on market outcomes are more difficult to measure directly since they may be more long term and are realized at the organizational level with several other factors also affecting these market outcomes.

To have organizational impact, the ultimate goal of MMSS, one has to ensure that the interests of the organization and the individual are aligned. Therefore, direct feedback of the effects of the MMSS on market outcomes should be presented to the MMSS user. The system should not only propose an optimal decision to its user but also explain why this decision would be best and what its consequences for the market performance of the organization would be (Kayande et al., 2009). Figure 6.3 summarizes the various MMSS Impact variables. We note that the order in which the Decision Process and Market Outcome categories are presented in Figure 6.3 is opposite to the order in which we introduced them above. The causal ordering between the variables is as presented in Figure 6.3, which describes the focal-dependent variable in our discussion. In a sequence of steps, we will now develop our model of the factors that drive MMSS impact, which will eventually result in the full model depicted in Figure 6.8.

6.1.1 Use of MMSS

To create impact it is necessary for the MMSS to be used by marketers (see Figure 6.4). More intensive use (i.e., doing more analyses) of the MMSS affects both decision processes and market outcomes. These analyses have a quantitative flavor in the case of data- and model-based

Fig. 6.3 Various measures for MMSS impact.

Fig. 6.4 The relationship between MMSS use and MMSS impact.

MMSS, and a qualitative flavor in the case of knowledge-based MMSS, and often concern considering the outcomes of alternative scenarios. The intensity with which the MMSS is used affects the amount of time they need to make decisions. However, working with the MMSS will also create a better understanding of the problem at hand and, consequently, lead to higher quality decisions to solve these problems. Finally, improved understanding will result from learning processes taking place when the decision maker interactively explores the outcomes associated with alternative courses of action. Thus, more intensive use of the MMSS leads to improved market outcomes. In terms of the effort-accuracy tradeoff (Payne et al., 1993) we expect more intensive use of the MMSS to require more cognitive effort but also to lead to decisions of higher quality, i.e., improved decision accuracy. Of course, the strength of the relationship between MMSS Use and MMSS Impact can be expected to be moderated by other variables, such as the quality of the MMSS. We discuss potential moderators later.

The decision to use the MMSS is often made by the individual decision maker. Only in the case of so-called mandatory use, top management will directly affect the intensity of MMSS use. Organizations thus depend on the decisions of individuals to start using systems to obtain effects at the organization levels. For these effects to appear, organizations can influence the behavior of individual employees. The most obvious but important way of stimulating the use of MMSS is by making them available to individual users. At the organizational level, the decision to adopt an MMSS thus has to be made first (see Figure 6.5).

6.1.2 Implementation Characteristics

As is shown in Figure 6.5, the organizational effects of an MMSS (i.e., its effects on market outcomes) are affected by decisions at the

Fig. 6.5 The relationship between MMSS adoption and MMSS impact.

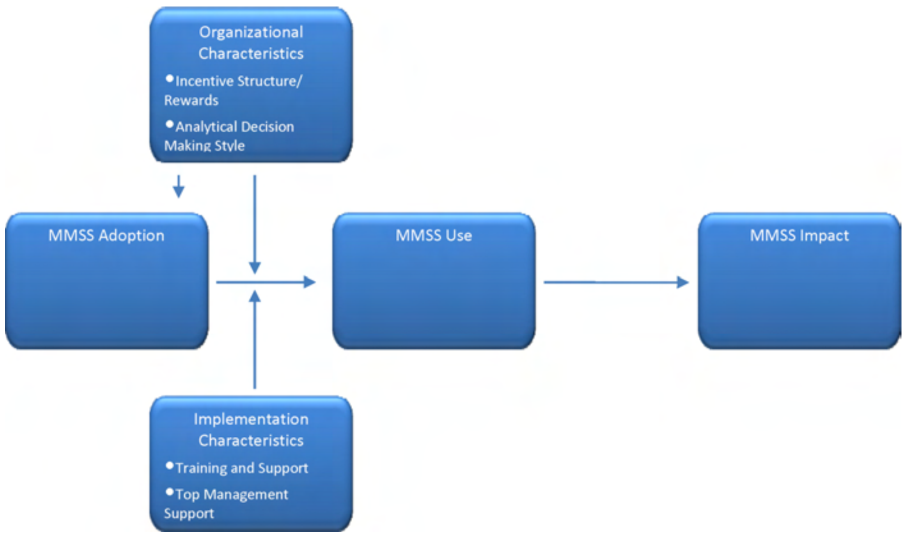


Fig. 6.6 The effects of organizational and implementation characteristics on MMSS use.

organizational level as well as by behavior of individuals within these organizations. The characteristics of the MMSS implementation procedure and of the organization affect the use of MMSS by individual users within these organizations. At the organizational level it is important to create the conditions that make sure that individual decisions (to start using MMSS and use it with sufficient intensity) are such that they contribute to the goals of the organization. Only if this is the case MMSS Adoption will successfully lead to MMSS Use (see Figure 6.6).

There is a large literature in the general IS/DSS field about the effects of *implementation characteristics* on the success of IS (e.g., Zmud, 1979; Alavi and Joachimsthaler, 1992a; DeLone and McLean, 1992). In the marketing literature, these implementation variables have also been shown to be important (e.g., Zinkhan et al., 1987; Wierenga and Oude Ophuis, 1997). Characteristics of the implementation process have been a long-standing concern for both decision support systems (Schultz and Slevin, 1972) and marketing models (Naert and Leeflang, 1978) and many studies have been conducted. We present a summary of the state of knowledge with respect to the most important implementation variables.

Top management support refers to the extent to which the superiors of the users support the development and use of Marketing Management Support Systems. There is overwhelming agreement in the (M)DSS literature that top management support is an important success factor for decision support systems (Zmud, 1979; Lilien et al., 1992; Gelderman, 1997; Wierenga and Oude Ophuis, 1997).

Training of the users of the Marketing Management Support Systems. In the diffusion of an information system within an organization, users are influenced by training (Leonard-Barton and Deschamps, 1988). In the context of information systems, training refers to the provision of hardware and software skills sufficient to enable effective interaction with the DSS under consideration (Alavi and Joachimsthaler, 1992a). Proper training of end users is an important strategy for minimizing resistance (Adams et al., 2004). Training appeared to have a significant positive effect on Marketing Management Support System performance in several studies (Barki and Huff, 1990; Alavi and Joachimsthaler, 1992b; Udo and Davis, 1992).

The quality of *user documentation* is also positively related to the effectiveness of Marketing Management Support System use (Torkzadeh and Doll, 1993). Gonul et al. (2006) show that confident and long explanations associated with MMSS advice can improve user acceptance of that advice. In the context of medical diagnosis of acute cardiac ischemia, Lai et al. (2006) found that a tutorial on the advice given by a clinical DSS increased the use of that advice by emergency care physicians, leading to better patient outcomes. Limayem and DeSanctis (2000) find that system explanations improve group DSS usability, particularly because of improvements in user understanding of decision models.

User involvement is the extent to which users, i.e., marketing decision makers participate in the design and maintenance of Marketing

Management Support Systems. User involvement is the most studied implementation variable in the DSS/IS field. In two recent meta-analyses relatively large positive effects of user involvement on system use and satisfaction with the system were found (Alavi and Joachimsthaler, 1992b; Gelderman, 1997). For *marketing management support systems* the importance of user participation and involvement of marketing in the purchase/development process of an MMSS was demonstrated in the study by Wierenga and Oude Ophuis (1997).

Communication about Marketing Management Support Systems to (future) users. For a marketing audience the importance of this factor will be clear, but in the DSS/IS literature communication this has not received much attention. In general, the number of information sources through which a company becomes aware of a new technology has been found to be an important factor for its adoption (Zaltman et al., 1973; Gatignon and Robertson, 1989). Imitative behavior also plays a role. Apparent success that other innovators have with a new technology is a motivation to adopt the innovation oneself (Swanson, 1994). It was found that the number of different information sources and knowledge about successful Marketing Management Support Systems applications in other companies are significantly related to Marketing Management Support Systems adoption (Wierenga and Oude Ophuis, 1997).

Marketing organization. The successful implementation of a marketing management support system requires a certain level of marketing development in the company, reflected by the presence of marketing expertise, and the existence of some form of marketing organization (a marketing department, use of an annual marketing plan, resources for marketing, and so on). It does not make sense to install an MMSS in an organization without a basic marketing organization. The presence of a marketing organization is significantly related to MMSS success (Wierenga and Oude Ophuis, 1997).

Presence of a Marketing Management Support Systems champion, a person who is seized by the idea of a Marketing Management Support System and who pushes it through the company. It has been found that the presence of a (marketing) management support system “champion” can have a very positive effect on its success (Sviokla, 1989; Wierenga and Oude Ophuis, 1997).

Attitude of the IS department. Almost always, the IS department is involved in the implementation of a Marketing Management Support System. This can be as the developer of the system or as a major advisor to (top) management if the system is purchased from outside. A cooperative attitude of the IS staff was found to be an important factor for (marketing) management support system success (Joshi, 1992; De Jong et al., 1994).

In-company developed versus purchased. The tradeoff between these two ways of realizing a Marketing Management Support Systems is between faster implementation and lower costs for a commercially purchased package and more flexibility and a better fit with the specific situation for a tailor-made customer-developed system (Lucas et al., 1988). The latter consideration would make one to expect a relative disadvantage for a commercially purchased package, but in the study by Wierenga and Oude Ophuis (1997) no difference in Marketing Management Support System success between the in-company developed and the purchased Marketing Management Support Systems was found.

6.1.3 Organizational Characteristics

Next to implementation characteristics, characteristics of the organization affect the extent to which individuals within the organization use the MMSS. The *incentive structure* within an organization affects the way MMSS will be used. The use of appropriate incentives is an important means of keeping people in an organization focused on customers (Day, 2003) and having them make decisions that improve the attractiveness of the organization's offerings in the eyes of customers. Reinartz et al. (2004) find that organizational alignment, including rewards for employees for building relationships with customers, shows positive effects on their behavior to accomplish this. If an organization rewards its employees for building relationships with customers, then it becomes instrumental for the employees of that organization to use the MMSS that have been adopted by the organization. That is because this will help them succeed in meeting the goal of improved customer relationships and make them eligible to receive the rewards.

The prevailing organizational *attitude* and approach to doing things (Pettigrew, 1979) and supporting decisions will also affect MMSS use. One can distinguish a more analytical approach using quantitative data and formal analyses to support decision making from a more heuristic/holistic approach. Data-based MMSS center around data and (quantitative) analysis, and we expect that such MMSS fit best in organizations that have an analytical/systematical approach toward decision making and that decision makers operating in these organizations are more inclined to use the MMSS that has been adopted by the organization.

6.1.4 User Characteristics

Next to organizational characteristics and implementation characteristics, we also expect user characteristics and system characteristics to affect the way the MMSS is used (see Figure 6.7) and moderate the relationship between MMSS Use and MMSS Impact. Several user characteristics can be distinguished. In part, these overlap with the individual characteristics that also favor using a certain marketing problem-solving mode (see Section 3.5.2) like *cognitive style,*

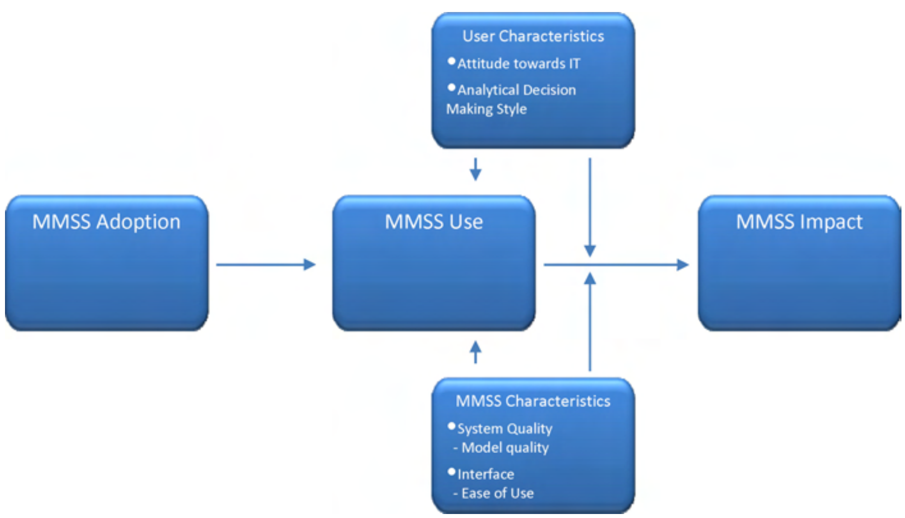


Fig. 6.7 The effects of system and user characteristics on MMSS impact.

marketing decision making experience and skills. Additionally, the general *attitude toward information technology* has been found to be an important explanatory variable for the use of specific information systems for a long time already. The theoretical basis for the effects of this variable lies in the context of the Technology Acceptance Model (Davis et al., 1989). Users with a more positive attitude toward the use of information technology for business purposes in general will also perceive specific MMSS as more useful and will experience higher satisfaction from using these systems.

6.1.5 MMSS System Characteristics

System characteristics clearly affect MMSS use and impact. We distinguish two categories of system characteristics. One category, *system quality*, deals with the "content" of the support that the system offers (i.e., type, quality, and sophistication of models and data, that is the information and insights the system produces), whereas the other category refers to the *interface*, i.e., the "package" through which the user has access to these functionalities of the MMSS. Here we think of user friendliness, flexibility, and adaptability of the MMSS.

Regarding the content (*system quality)*, Wierenga and Van Bruggen (1997) and Wierenga et al. (1999) argue that in order to get the system adopted by the user, the way the MMSS provides support should match with the way the marketer makes decisions. Wierenga and Oude Ophuis (1997) report a positive relationship between systems sophistication and system impact. Van Bruggen et al. (1996) also find that decision makers who use better MMSS (i.e., systems that contain better models) make better decisions. More sophisticated, higher quality MMSS moderate the relationship between MMSS Use and MMSS Impact in the sense that a more intensive use of a higher quality system has a more positive effect on its Impact. As we already observed, research in Marketing (Science) over the years has produced a large collection of high-quality models, which can be components of MMSS. This quality of MMSS continues to increase. Unfortunately, there is no evidence that better systems are also used more intensively. The study by Van Bruggen et al. (1996) shows that decision makers have difficulties in recognizing and valuing the quality of the systems they use and they do not find evidence for a more intensive use of better systems. The lack of a relationship between MMSS quality and MMSS use means that an increase in the quality of systems does not cause MMSS Impact to increase as much as would be potentially possible.

If we look at the system *interface* or the *packaging* of the MMSS more user-friendly systems are used more intensively. The extent to which a system is perceived to be user-friendly strongly depends on how easy-to-use users perceive the system to be. Research of Davis (1989) indicates that a system's ease of use increases its use. Ease of use is the degree to which a person believes that using an information system would be free of effort. It is one of the "classical" concepts in information systems research (Davis, 1989; Venkatesh, 2000; Sanders and Manrodt, 2003). A significant body of research in information systems cumulatively provides evidence for an effect of perceived ease of use on initial user acceptance and sustained usage of systems (Venkatesh, 2000). The Technology Acceptance Model (TAM) (Davis, 1989) suggests perceived ease of use to determine one's behavioral intention to use a technology, which is linked to subsequent actual use. TAM also suggests that ease of use influences perceived usefulness because the easier a technology the more useful it is (Venkatesh, 2000). Flexibility, also called adaptability, is another critical factor explaining the success of information/decision support systems (Little, 1970; Barki and Huff, 1990; Udo and Davis, 1992). Flexible systems can be adapted more easily to the changing requirements of the decision situation and the specific needs of its users. This also enhances their use and as a consequence their impact.

Goodman (1998) and Wigton et al. (1986) show that the *feedback* that an MMSS provides its user with can play both an informational role (promoting knowledge acquisition) and a motivational role (providing a reward-cue for increasing cognitive effort investment). This feedback is thus additional information on top of the actual recommendation, suggestion, or diagnosis, which an MMSS provides its user with. Kayande et al. (2009) show that a *dual-feedback* MMSS, one that incorporates feedback *both* about upside potential (i.e., how much more can be gained by internalizing the DSS model) *and* feedback on corrective actions (i.e., guidance on how the manager's mental model should be corrected), induces more effort from decision makers as well as offer appropriate decision guidance. This combination of effort and guidance then produces significant mental model updating; while single feedback MMSS produce little or no updating. Mental model updating, in turn, leads to better subjective DSS evaluations than when little or no mental model updating occurs. While many MMSS incorporate some form of feedback, these results show that MMSS evaluations only improve after significant mental model updating, which occurs when the MMSS incorporates *both* upside potential and corrective feedback. Kayande et al. (2009) empirically demonstrate that deep learning (i.e., the transformation of mental models) is crucial for managers to form a favorable evaluation of an objectively high-quality MMSS. Their study shows that an MMSS that provides upside potential feedback can motivate managers to perform better, resulting in greater effort. However, increased effort alone is not sufficient to generate deep learning; the MMSS must also provide clear guidance about how and why a modification of a mental model leads to a superior outcome. Their results also show that mere shallow learning does not lead to better evaluations of MMSS, implying that MMSS that offer no opportunity to understand their recommendations are likely to be poorly evaluated by users and hence, used less frequently. Hence, that a *dual-feedback approach*, combining upside potential and specific guidance is required to help managers internalize and be able to take advantage of the MMSS. MMSS feedback is also found to influence users' underlying learning processes, which in turn, helps users internalize the relationship between decisions and outcomes. While much prior research has examined decision outcomes, the Kayande et al. (2009) study enriches the story by showing how objectively superior MMSS can also be perceived more positively. To improve user recognition of MMSS value, the MMSS should stimulate its users' learning processes by providing "dual-feedback" in an interactive manner. Such feedback is also likely to influence effort-accuracy tradeoff (Todd and Benbasat, 1999) in favor of more accurate decisions and better performance. Effective feedback is thus an important driver of MMSS evaluations.

6.2 Dynamics in MMSS Perceptions

MMSS use and the resulting decision making processes and market outcomes may lead to revised perceptions of the value of systems, in particular their Perceived Usefulness. Therefore, a model of MMSS Impact should incorporate feedback loops, the importance of learning and the revision of beliefs about the usefulness of MMSS (Seddon, 1997). In Figure 6.8 we present our comprehensive model of MMSS Impact, which contains these feedback loops. Once decisions have been made and implemented appropriately, (objective) market outcomes will be realized. Decision makers also have a certain perception of the quality of the decisions they made. This is reflected in the amount of confidence they show in their decisions and their satisfaction with these decisions. Similarly, decision makers have a perception of the value of the MMSS they used when making their decisions. This will be reflected in, for example, updating the Perceived Usefulness (Davis, 1989) of the system. A relationship between the evaluation of the decisions made

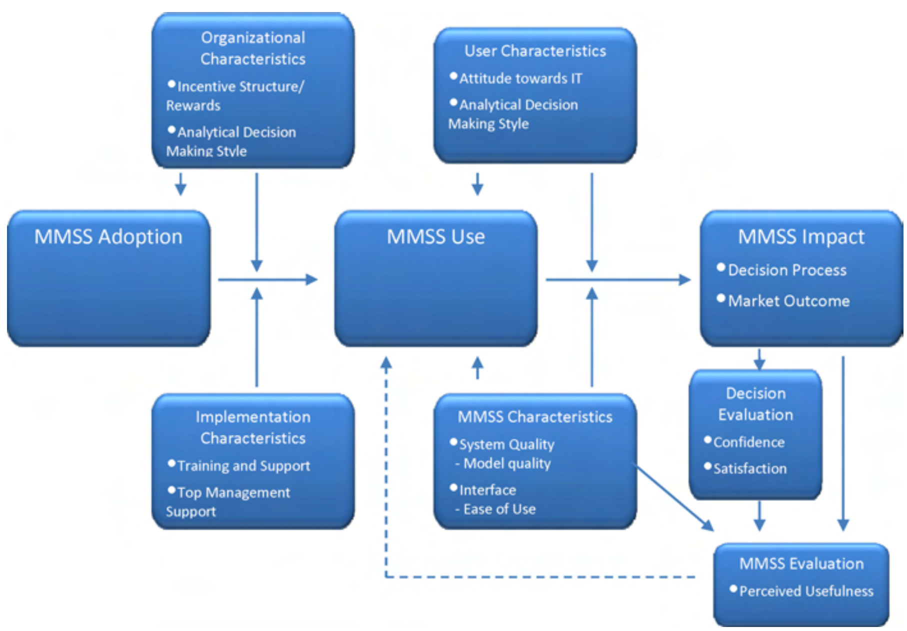


Fig. 6.8 Overall model that describes the drivers of MMSS impact and its dynamics.

and of the use of the MMSS also exists. If decision makers perceive the quality of their decisions to be good this is (partly) attributed to the MMSS. Decision makers who are satisfied with the decisions they made using the MMSS also evaluate the system more positively. Consequently, these decision makers are also more inclined to use MMSS again in future decision situations.

In this section we have addressed the impact of marketing management support systems. As we have seen, most of the empirical studies on the impact of MMSS show that when these systems are used, they actually improve the quality of decision making leading to better market outcomes. At the same time, many authors (e.g., Little, 1970; Eliashberg and Lilien, 1993; Simon, 1994) have observed that these systems have not fulfilled their potential. How can we use the model of Figure 6.8 to solve this discrepancy? *The* key factor for creating MMSS impact is to get these systems used by individuals once they have been adopted by the organization. Several factors stimulate MMSS use. For example, management plays a key role because by rewarding individual decision makers for using systems and by creating a decision making style and culture in the organization in which MMSS use is a logical thing to do. Also, they should make sure that a system is not simply "dropped" in the organization but that appropriate implementation procedures are in place. Furthermore, it is also important that the characteristics of the people who are supposed to use the MMSS match with the types of systems that have been implemented in the organization. Either systems should be selected that match with the nature of the decision making style of the marketers that are employed, or top management should recruit managers that have a decision making style that matches with the nature of the available MMSS. Furthermore, the systems should be of high quality and the interface should be user-friendly.

Getting individual marketers to using MMSS requires endurance. As we have seen earlier, research (Lilien et al., 2004) shows that individual decision makers have difficulties in recognizing the value of systems. If users do not recognize the quality of MMSS this hampers their impact because systems will not be used as intensively as would be desirable. Especially the intensive use of high-quality systems leads to superior organizational outcomes. By implication, limited use of such systems leaves a lot of potential unrealized. In order to make decision makers realize the positive impact of MMSS on the quality of their decision making a learning process needs to take place. Only by actually using systems and observing its benefits leads to the realization of their potential. Users may not immediately be enthusiastic or confident about an MMSS once it has been implemented. By encouraging decision makers to consider decision alternatives they did not consider before (by enlarging their solution space) is one of the main benefits of MMSS (Van Bruggen et al., 1998). However, doing things differently may create uncertainty. It is important to anticipate this aspect and carefully guide users to make sure that they continue using systems for a longer period of time. There is a concrete risk that decision makers reduce the intensity with which they use an MMSS or completely quit using the system after initial enthusiasm (Speier and Venkatesh, 2002). Providing decision makers with feedback about the way the MMSS works and how it adds to the quality of decision making is, therefore, essential.

7

Perspectives for Marketing Management Support Systems

In this final section we reflect on a number of issues and developments relevant for the future of marketing management support system.

(1) The opportunities for decision support systems in marketing have greatly improved. Nowadays, many marketers operate in environments that are highly conducive to the use of marketing management support systems. There is enormous data richness and many tools, often embedded in company-wide information systems, are available to process these data and use resulting insights for the support of decision making activities. We have described the development of marketing management support systems over time and have seen that a rich collection of systems has thus become available. Two important drivers behind these advances in marketing management support systems are: (1) the developments in information systems and information technology and (2) the developments in marketing science. Developments in information technology and information systems have greatly improved the means to collect and store data. For example,

scanning technology and the possibility to track people's click paths when they are browsing the Web have led to detailed data about people's information search and purchasing behavior. Increased storage capacity has made it possible to store all these data and increased computing power has made it possible to analyze data using sophisticated methods. Research in marketing science has exploited these advances in information technology and information systems and marketing scientists have developed increasingly sophisticated models and methods that provide marketers with insights about customer — and competitor behavior and that also provide them with the possibility to support their decisions. Today, a marketer typically has several databases and spreadsheet programs available that are used to monitor sales, market shares, distribution, marketing activities, actions of competitors, and other relevant items. Such systems are either made in-house, i.e., by the firm's own IT department, or made available by third parties. Providers of syndicated data such as Nielsen or IRI, typically make software available for browsing large databases, and for the performance of specific analyses. For the adoption and use of MMSS it is an important advantage that marketing managers are fully connected to an IT system. When a new MMSS is to be introduced, the "distribution channel" to the marketing manager (i.e., the platform) is already there. In this way, using the MMSS becomes a natural part of the (daily) interaction with the computer. One step further, marketing decision support tools are not separate programs anymore, but have become completely embedded in the overall IT infrastructure that managers are connected with and use (see Lilien and Rangaswamy, 2008). The potential impact of marketing management support systems has thus grown over the years and is substantial nowadays. Research on marketing management support systems studies how the potential of marketing management support systems can be translated into real impact on the practice of marketing management and marketing decision making.

(2) Research on marketing management support systems has already developed into an independent research domain, but more effort is needed Substantial research efforts (Little, 1970; Wierenga and Van Bruggen, 1997, 2000; Van Bruggen et al., 1998; Wierenga et al., 1999; Lilien and Rangaswamy, 2004, 2008; Lilien et al., 2004; Kayande et al., 2009) have been put into identifying the factors and conditions that drive the impact of marketing management support systems. In order to have impact on the performance of organizations it is necessary for MMSS to be used by the (individual) marketers employed by these organizations. To make this happen these marketers have to be incentivized and have to recognize the value of these systems. Especially recognizing the value of MMSS doesn't seem to be a trivial thing for marketers as research has shown that they have difficulties in recognizing this value (Van Bruggen et al., 1996; Lilien et al., 2004). Therefore, education, training, and communication are important for the further dissemination and use of marketing management support systems. Developers and designers of MMSS also have to be aware of the value of communication and they will need to incorporate it *into* the systems they are building. Research (Kayande et al., 2009) has shown that systems that provide their users with appropriate feedback will be evaluated more favorably and, therefore, more likely to be used. This means that MMSS should no longer operate as "black-boxes" providing the marketer with suggestions without the logic behind it but should explain their recommendations. Advancing knowledge and insights into what makes people recognize *and* acknowledge the value and usefulness of MMSS is an important field for further research.

(3) MMSS are part of the daily life of marketing decision makers. Therefore, the use of these systems should be an integral part of business school curricula in marketing. Training and teaching tools like the Marketing Engineering Software (Lilien and Rangaswamy, 2004, 2008) are extremely useful for teaching

future marketers how to use MMSS in marketing practice. However, we should make sure that MMSS are not seen by these users as an interesting topic in itself, separate from the day-to-day marketing management problems that have to be solved. Therefore, we are not in favor of independent courses on MMSS and Marketing Engineering, but we think that these tools should be an essential part of any marketing management and marketing strategy course. Every case in a marketing management course should be accompanied with an MMSS helping the student to find a solution. This will create the habit of using these systems in an interactive way (see Figure 1.1) and thereby getting the best out of the combination of the marketing decision maker and the MMSS.

(4) The third marketing era, with its focus on the individual customer, offers enormous possibilities for MMSS. Earlier in this contribution, we discussed the development of Customer Relationship Management (CRM). In principle, every CRM system is an MMSS, and the adoption and diffusion of CRM systems in companies is going very fast.

Traditionally, data in marketing management support systems, and also in CRM systems have been quantitative in nature. Through the use of scanning technology, web surveillance, and customer relationship management technologies large amounts of quantitative data about purchases, prices, information search, and customer contacts can be gathered. Most models and methods that have been developed aim at processing and analyzing these types of data. However, with the advent of social media like Blogs, Facebook, Twitter, Virtual Communities, and Discussion Forums (De Valck et al., 2009; Kozinets et al., 2010) a wealth of new data has become available. These data are mainly *qualitative* in nature. Customers increasingly share their attitudes, intentions, and experiences about products, services, and suppliers with other customers and actively approach organizations and individuals with the questions they face. Potentially, these data offer a wealth of customer and competitive information and tools and methods are needed to capture such qualitative data, process them, and transform these data into actionable insights. Knowledge-based marketing management support systems are suited for these kinds of tasks. Therefore, the advent of social media calls for renewed research into tools and methods for the analysis of qualitative data and transforming these into knowledge-based marketing management support systems. One can argue that the traditional distinction between data-driven and knowledge-based MMSS is disappearing and that future systems will combine both types of data and information, merging the two actionable insights from both sources and make recommendations for marketing management. So-called *social* customer relationship management support systems are a case in point.

(5) There is an increasing emphasis on the contribution of marketing to the bottom-line results of a company (Hannssens and Dekimpe, 2008). Marketing management support systems often aim at providing marketers with an "optimal" solution for a problem at hand. For example, how to allocate a communication budget across various media or allocate a sales force across multiple channels and customers or whether or not to change a price and with how much. Increasingly, marketers are forced to provide insight into and evidence for the anticipated (financial) outcomes of their marketing activities and decisions (Srinivasan and Hanssens, 2009). Therefore, MMSS that provide information on the return on marketing (ROM) of their activities will be an asset for marketers and help them making marketing accountable. This in turn will improve the position of marketing within companies (Verhoef and Leeflang, 2009). To realize this, it will become increasingly important that *marketing* management support systems are embedded in the broader management support systems that organizations have in place (Lilien and Rangaswamy, 2008). The increasing emphasis on marketing accountability is a driving force behind the demand for more, better, and easily accessible MMSS. Marketing Dashboards,

discussed earlier, can provide quick overviews of what marketing accomplishes for a company in terms of sales, profits, and ROI, at an overall level, but also for different products, different business units, and different geographical regions.

(6) There is a continuing discussion about the question whether marketing management support systems should replace *or* support marketers. Bucklin et al. (1998) presented a vision for 2020 where they foresaw a shift from decision support to decision automation for certain decision tasks. We feel that a distinction should be made between tactical decision making and (marketing) strategy development. Increasingly, customer will use new technologies such as the Web and smartphones equipped with GPS technology (e.g., Apple's IPhone and Google's Nexus) through which they connect continuously to companies, friends, and markets. For companies it will become critical to identify the opportunities in time and place where customers are looking for information or are interested in a transaction and respond instantaneously with an offer the customer will be interested in. Mobile marketing has, finally, become reality. For these tactical tasks, companies will need to have systems in place that identify opportunities and respond to them in real-time. This calls for systems that automate part of the marketing process. Using the description of the marketing decision making process as presented in Figure 1.1 this means that data and information will be fed into marketing management support systems which in turn will take marketing actions without the consultation of or intervention by a (human) marketer. Automation of these tasks will be necessary because the frequency with which decision situations will present themselves will be so high that it will no longer be possible to have human marketers deal with these situations. For developers of marketing management support systems these decision situations offer great opportunities and the challenge lies in designing systems a marketer can rely on unconditionally. Since these decision situations appear so frequently, it should

be possible to develop such systems and fine-tune them using feedback from the market.

For more strategically oriented decision tasks that appear less frequently the active involvement of human marketers will stay necessary. Marketers will not want to automate such decisions and it can be argued that such automation is not possible either. The *combination* of the decision maker *and* the MMSS and the interaction between the two (see Figure 1.1) is the recipe for optimal outcomes. In order to make marketers and organizations accept this idea, systems that complement the human decision maker's competencies and skills and are aligned with his/her decision making style at the same time will be needed. The latter will be necessary to increase the acceptance of MMSS in practice. It will be a challenge for designers of marketing management support systems to design these systems in such a way that they meet these needs.

(7) There is a big gap between the scientists who develop analytical marketing tools and the practitioners who are expected to implement and use them. We all know the huge difference between the world of academics who like to analyze and solve problems in a thorough and solid way and the world of managers whose activities can be characterized by brevity, variety, and discontinuity (Mintzberg, 1973). It is easy to blame the model builder for being more interested in the model than in its application, and the practitioner for not immediately embracing those wonderful models. However, it is more realistic to admit that often the implementation is beyond the expertise, incentive systems, and available time of each of these two parties. An interface in the form of a marketing management support system is needed as the missing link between science and practice. The development of successful marketing management support systems requires a separate type of experts: people who understand marketing decision problems good enough to see what the manager needs, and at the same time have sufficient technical skills to

turn models into working decision support systems. We might call them "marketing engineers". The success of a marketing management support system is dependent on a large number of variables (Wierenga et al., 1999), for example the type of organization and its decision making culture, the dynamics of its markets, the availability of data, the decision support technology applied (e.g., models, expert systems, or neural nets), design characteristics of the system (user interface, accessibility, flexibility), and how the system is implemented (user involvement, top management support, training). It takes thoughtful and deliberate consideration and advanced marketing engineering capabilities to design and implement a marketing management support system that successfully bridges the gap between model and decision maker in a particular situation (Eliashberg et al., 2009b).

Considering all the developments discussed in this section, we expect a strong growth of marketing management support systems, in their availability, their capabilities, and their contribution to the quality of marketing decision making and the practice of marketing management.

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