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The powerful triangle of marketing data, managerial judgment, and marketing management support systems

Gerrit H. van Bruggen, Ale Smidts and Berend Wierenga
Rotterdam School of Management, Erasmus University Rotterdam, The Netherlands

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Abstract *Conceptualizes the impact of information technology on marketing decision making. Argues that developments in information technology affect the performance of marketing decision-makers through different routes. Advances in information technology enhance the possibilities of collecting data and of generating information for supporting marketing decision making. Potentially, this will have a positive impact on decision-making performance. Managerial expertise will favor the transformation of data into market insights. However, as the cognitive capabilities of marketing managers are limited, increasing amounts of data may also increase the complexity of the decision-making context. In turn, increased complexity enhances the probability of biased decision processes, thereby negatively affecting decision-making performance. Marketing management support systems, also being the result of advances in information technology, are tools that can help marketers to benefit from the data explosion. The analysis leads to the expectation that the combination of marketing data, managerial judgment, and marketing management support systems will be a powerful factor for improving marketing management.*

Introduction

In recent years, marketing has been heavily influenced by developments in information and communication technology. Technological developments, such as the introduction of barcode scanning and the Internet, provide marketers with enormous amounts of data. The availability of more and better data should offer opportunities to marketing decision-makers to make better-founded decisions. At the same time, it confronts decision-makers with the issue of how to process and incorporate all of these data in their decision-making processes. Managers, nowadays, see perhaps 1,000 times the volume of data (more frequently collected in finer detail) they saw five years ago. The human brain, however, has not become comparably more powerful in the same period. More data cannot lead to better decision making, unless managers learn how to exploit those data in meaningful ways (Lilien and Rangaswamy, 1998, p. xiii). This means that, if, for example, marketers in fast moving consumer goods industries are offered weekly AC Nielsen data instead of receiving them once per four weeks, this will not automatically improve their decision

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performance. Potentially, weekly data in themselves can offer more market insight than monthly data. However, it depends on the cognitive capacity of the marketer and of the (decision support) tools that he or she has available whether more detailed data will improve decision performance rather than lead to a situation of information overload and biased decisions. In deciding about whether to buy weekly or monthly data, marketers will have to consider these factors.

The availability of more marketing data has both benefits and costs (Payne *et al.*, 1993). A benefit of more data is that it will positively affect the possibility of attaining decision accuracy. However, processing more data will also require more cognitive effort. According to Payne *et al.* (1993) individuals intelligently trade off accuracy and effort. That is, decision processes will reflect a reasonable compromise between the desire to benefit from more data and the desire to minimize cognitive resources used in exploiting data and making decisions. This leads to the contingent use of heuristics (e.g. simplifying strategies that are more selective in the use of information (Payne *et al.*, 1993)). The outcome of the trade-off, and thus the use of the heuristics, will be contingent upon a variety of task, context, and individual difference factors. Thus the net effect of more marketing data on decision performance will be a function of the benefits and costs.

In this paper we analyze the impact of increasing amounts of marketing data on decision performance. We argue that marketing management support systems are tools that can help decision-makers to effectively cope with and benefit from the data explosion. Each of the three components: marketing data, managerial judgment, and marketing management support systems, has its particular strengths and weaknesses, as will be described in this paper. In combination, the strengths of the individual elements will be reinforced and their weaknesses will be compensated for. Therefore, the combination of the three elements is expected to be especially powerful.

The purpose of this paper is to show how marketing management support systems make marketers benefit more from the availability of new data sources. In Figure 1 we graphically show the relationship between the amount

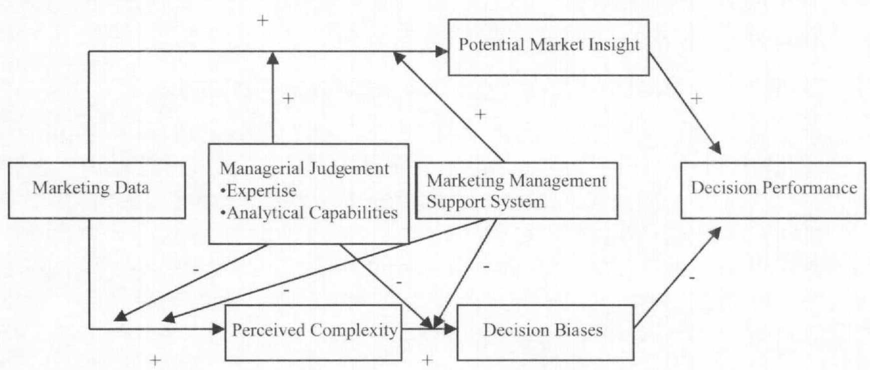

Figure 1. How more marketing data affect decision performance

of data and decision performance and how this relationship is affected by managerial judgment and the availability of marketing management support systems.

The effectiveness of marketing management support systems

In the marketing science literature the work put into the development of marketing management support systems relative to the effort spent on investigating their effectiveness has been modest. A number of (field) experiments was conducted; however, the results of these experiments were not conclusive. For example, Fudge and Lodish (1977) investigated the effects of the use of the CALLPLAN model (1971) by sales managers of United Airlines for determining optimal sales-call frequency schedules. They reported that the use of this model led to significantly higher sales. A confirmation of this effect was found for a similar sales-planning system in the pharmaceutical company Syntex (Lodish *et al.*, 1988). In a laboratory setting Chakravarti *et al.* (1979) found that the use of a marketing model did not improve the quality of marketing decisions. In fact model users made even poorer decisions. However, McIntyre (1982) reported an opposite finding in a laboratory setting: in his study MMSS users did perform better. Not only in marketing were inconclusive findings on the impact of information systems reported. Review articles of Sharda *et al.* (1988) and Benbasat and Nault (1990) show that in general the effects of information systems have been mixed. Therefore, insight into the question of what makes an information system effective is necessary.

As early as in the early 1970s in the information systems literature several researchers such as Chervany *et al.* (1972), Lucas (1973), Mason and Mitroff (1973), and Mock (1973) studied the question of the effectiveness of information systems. They developed theories or frameworks that described the factors that affect the effectiveness of an information system. Summarizing their work, we can identify four sets of factors that determine how effective an information system is. These factors are the characteristics of:

(1) the information system itself;

(2) the decision-maker who used the system;

(3) the problem which is being solved; and

(4) the environment in which the decision-maker is operating.

Eierman *et al.* (1995) conclude that of all the different possible combinations of factors that can be studied only half have actually been studied. They plead for fuller DSS research models to understand contingencies and thus the mechanisms through which an information system works. This means that it is no longer sufficient to know which factors affect the success of information systems but that knowledge is needed about the process through which information systems affect decision making, i.e. why (Barr and Sharda, 1997) and how they affect decision making.

Some papers shed light on this issue. Hoch and Schkade (1996) and van Bruggen *et al.* (1998a) show that decision-makers tend to apply a so-called pattern matching approach, in which they focus especially on the similarities between a problem at hand and previous situations they have experienced. This strategy works well in stable environments but might be less effective in turbulent environments. In such a situation an information system can be effective, because it can make decision-makers less susceptible to decision biases. Barr and Sharda (1997) also study why decision support systems are effective. They find that systems are especially effective because of what they call a reliance effect. This means that decision quality increases because of decreases in computational errors. In this paper our aim is to develop an understanding of how marketing management support systems work for certain types of decision-makers in data-intensive environments. This meets the call of Eierman *et al.* (1995) for research to gain insight into the contingencies or interaction effects that affect DSS effectiveness. In our case this concerns the interaction between the functionality of a marketing management support system, the decision-maker's characteristics, and the decision-environment variable data availability. We will now proceed with describing the developments in the availability of marketing data and their impact on decision making.

Marketing data

Nowadays, more detailed marketing data about more marketing variables are becoming available. Several reasons for this "data explosion" exist. First, in consumer markets the adoption of scanning technology has been one of the major drivers behind this development. The installation of systems that capture point-of-sale data (POS) has probably been greatest in the supermarket segment. The initial impetus for retailers to install sophisticated POS was to decrease the time that was required to record the items purchased by customers and to improve the accuracy of checkout processes (Ing and Mitchell, 1994). However, besides using these data for improving the efficiency of logistical processes, their availability also led to opportunities for a more systematic approach to marketing activities, especially when this information is combined with the information stemming from frequent shopper programs. This way, shopping behavior of individual customers can be monitored and linked to their background characteristics (single-source data). Nowadays, data on purchasing behavior have become available on a weekly basis. This means that manufacturers can more accurately determine what the results of, for example, promotional programs are and what the consequences of price changes are. Being able to accurately determine the relationships between marketing-mix variables and outcome variables leads to enhanced opportunities to develop more effective promotional programs and attractive product propositions for specific market segments.

Not only in consumer markets but also in business-to-business markets, data increasingly are collected in a systematic manner. Salespersons are equipped with laptop or hand-held computers and the adoption of sales information and support systems has led to systematic collection and storage of information about customer contacts and their results. By analyzing these results, it is possible to determine the effectiveness of actions in the past. Furthermore, these data create possibilities for determining which way of approaching (potential) customers is most effective in which situation.

The development of the Internet seems to lead to another "data revolution." More and more online vendors trace information-search and purchasing behavior of customers who visit their Web sites (e.g. www.amazon.com and www.cdnow.com). Customers that visit Web sites are identifiable and background characteristics from these persons can be linked to their actions. This enables one to actually determine what kind of information different types of people look for, in what order (e.g. do consumers process information by brand or by product?), and which products are seriously considered before a purchase is made. This type of detailed information on pre-purchase activities, that has not so far been available, can be effective in developing marketing programs.

Finally, organization-wide information systems (e.g. ERP systems) enhance inter-departmental information sharing. Hence, marketers get access to data from, for example, the finance or the production department. This further increases the availability of data for the support of marketing decision making.

Data from different sources (such as transactions data, data on marketing actions, external data purchased from direct marketing companies, and from retailers and consumer-panels) can be put together in so-called data warehouses. The primary aim of a data warehouse is to make data easily available and accessible for decision support.

The increased numbers of sources of data that have become available to marketers for their decision making have led to a situation in which, potentially, better market insights can be derived about the relationships between relevant marketing variables. A marketer's market insight concerns the extent to which the marketer knows what happens in the market, why it is happening, what would happen if he or she were to perform some kind of action and what he or she should do to reach certain goals. More marketing data make the information on which decisions have to be based more valuable and can thus increase the insight of the marketer. (Using the definitions of Lilien and Rangaswamy (1998), we make a distinction between, on the one hand, marketing data and, on the other hand, information and insights. They define data as facts, beliefs or observations used in making decisions. Information refers to summarized or categorized data, while insights provide meaning to the data (p. 4)). If, for example, a marketer receives data on sales in addition to data on advertising expenditures, the quantity of marketing data increases. Having data on these two variables makes it possible to develop insights into the relationship between advertising and sales. Similarly, obtaining data on these two variables more frequently makes it possible to develop an even more accurate idea of the relationship between these variables and will thus further increase the (quality of) marketing insights. Therefore, we propose that:

P1: More marketing data lead to greater potential market insight.

Advances in information technology have thus led to a more accurate collection of data on large numbers of marketing variables and low aggregation levels. One would be inclined to unconditionally think "the more data and information, the better." After all, with all these data decision-makers should be able to develop marketing programs that are precisely targeted at (potential) customers. However, nowadays the abundance of data threatens to become a problem in itself, maybe even bigger than a lack of information. Reuters Business Information (Oppenheim, 1997) introduced the term Information Fatigue Syndrome (IFS) to refer to a situation in which decision processes of marketing decision-makers are negatively affected by "information overload." Information is collected on an ever-increasing regular basis. For example, Nielsen data were reported on a bimonthly basis only five years ago. Now they are available on a monthly or weekly basis and (soon) it will technically be possible to provide marketers with scanning information on a daily or hourly basis. As argued above, a lower aggregation level of these data permits the development of more potentially insightful information. However, it also leads to a situation where marketers have to process more and more information. According to an investigation by Andersen Consulting (O'Connor and Galvin, 1997) the number of data points increased from 8 million in the 1960s to 300 million in the 1990s. Ing and Mitchell (1994) calculated the number of POS data generated at the retail level. A single store may generate around 50,000 transactions per day and the typical size of a retail marketing database with weekly movements, SKU by store, will be in the order of 12 to 16 gigabytes. As opposed to the opportunities offered by the available data (as expressed in *P1*), it is felt that drawbacks also exist, because it confronts human decision-makers with increased complexity. Marketers will perceive their environment as being more complex, if they distinguish more relevant alternatives and attributes or variables (Payne *et al.*, 1993) and more interdependencies between these variables (Lawrence, 1981). Therefore, we propose:

P2: More marketing data lead to greater perceived complexity.

The marketer

Managerial judgment has always been seen as one of the most important assets, if not the most important, of marketers. The ability to judge both formal and informal information, to analyze data and to be creative in transforming information into effective marketing programs is a characteristic of successful marketers. Excellent marketers have powerful mental models, representations of markets and marketing processes in their minds. They use these mental models for the interpretation of and reasoning about events in the market. In this paper we focus on two elements of managerial judgment: managerial expertise and analytical capabilities.

Shanteau (1988) mentions several advantageous characteristics of experts in general that also apply to marketers as human decision-makers. Experts have extensive and up-to-date content knowledge, have highly developed perceptual abilities, know what is relevant when making decisions, can simplify problems, can communicate their expertise to others, handle adversity better than non-experts, and know how to adapt their decision strategies to changing task conditions. Furthermore, Shanteau (1992) found that experts differ from novices not so much in the amounts of information they use as in the type of information they use. They are better in including the most relevant information (on diagnostic and predictive cues) in their decisions. These characteristics of experts favor the transformation of data into marketing insights. Therefore, we propose that:

P3: More managerial expertise strengthens the relationship between marketing data and potential market insights.

The findings of Shanteau (1988, 1992) also provide evidence that more expertise and experience will reduce the impact of more marketing data on perceived complexity. Experts will be better in dealing with large amounts of data and will not perceive a data-intensive situation as being as complex as non-experts. Therefore, we propose:

P4: More managerial expertise weakens the relationship between marketing data and perceived complexity.

However, the cognitive abilities of the marketer alone may become inadequate, when confronted with the size of the data streams of today. The information flood can create situations with so much complexity for marketers that their decision quality suffers because of both biased information acquisition and biased information processing.

Information acquisition

Biased decision processes become prevalent when complexity leads marketers to focus on the information that is most easily accessible or available (Glazer *et al.*, 1992) instead of the information that is really needed to develop optimal solutions. So marketers will, for example, tend to focus on information about prices, when this is the information they are provided with, even if price is not an important factor for market success. Glazer *et al.* (1992) found this phenomenon to lead to sub-optimal decision making by marketers. Complexity may also lead to selective perception and the framing of decision problems in a way that is more dependent on a person's background than on the characteristics of the decision problem. Dearborn and Simon (1959), for example, found that the functional background of managers influences the way they perceive a problem. In their study one and the same business problem was perceived as a marketing problem by marketing managers, as a financial problem by finance managers, and as a logistical problem by logistics managers. A similar phenomenon was reported in the replication study of Beyer *et al.* (1997). According to Bruner, subjects, when presented with a complex stimulus, perceive in this stimulus what they are "ready" to perceive. The more complex or ambiguous the stimulus, the more the perception is determined by what is already "in" the subject and less by what is in the stimulus. van Bruggen *et al.* (1998b) found evidence for the same phenomenon for decision-makers within the marketing field. In a simulated setting, experienced decision-makers tended to focus on specific variables (e.g. price, advertising budgets, or salesforce) in processing information and when making decisions. The choice of the variables on which they focused depended more on the experience of the marketers than on the characteristics of the situation in the simulation. When confronted with large amounts of "fresh" data, these experienced decision-makers did not seem to challenge and subsequently revise their mental models in a way that led to an adaptation of these models to the new situation. The insufficient adaptation of mental models can be explained by findings of Klayman and Ha (1989) that point out that the process of hypothesis testing underlies many classes of human judgment. People form hypotheses about how their world works and use evidence gathered from experience to test and revise their hypotheses. However, results of experiments indicate the predominance of a positive test strategy that often leads to hypotheses that are too narrow. In this strategy subjects look for possible errors by testing instances they believe should fit the rule, with relatively few tests they believe should not. Successful problem solvers, however, are much more likely to direct their tests toward distinguishing explicit alternative hypotheses. It has been suggested that the key to successful hypothesis testing lies not so much in confirmation versus dis-confirmation *per se* but in the effective use of alternative hypotheses. Furthermore, hypotheses need not only to be tested but also to be revised.

Finally, in processing information decision-makers operating in complex decision environments might overestimate the value of concrete (qualitative) information (e.g. concrete experiences) at the cost of base-rate information (summaries, statistical information) (Hogarth and Makridakis, 1981). For example, marketers might attach too much value to the pricing instrument when they remember a very successful previous price action and neglect the results of a more general analysis of the results of pricing actions in the past.

Information processing

Complexity affects not only information acquisition processes, but also information processing activities. It makes it more difficult for marketers to consistently judge information (Dawes, 1971) and to revise opinions on the receipt of new information to the extent that Bayes' theorem implies (Hogarth and Makridakis, 1981; Glazer *et al.*, 1992). Furthermore, marketers may become more susceptible to heuristics because these reduce mental efforts. Specific examples of heuristics that are used by marketers are the use of "rules of thumb" and the anchoring-and-adjustment heuristic. Simon (1957) suggests that human beings develop decision procedures labeled with the term satisficing or rules of thumb (Bazerman, 1994). Examples of the use of rules of thumb by marketers are, for example, setting the advertising budget at a fixed percentage of sales revenues or always following price changes of the market leader. Another heuristic typically employed in making judgments under uncertainty is adjustment from an anchor (Tversky and Kahneman, 1974). Decisions are made by anchoring on the previous decision and are then adjusted with a certain percentage. In the case of marketing decision making with respect to advertising decisions, one could think of the example of taking last year's decision on the advertising budget as an anchor and setting the new advertising budget by adding a small percentage to this anchor. The adjustments to the anchor point often are 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).

Heuristics can be an economical way of allocating scarce cognitive resources. Payne *et al.* (1993) even call their use an intelligent way of responding adaptively to different decision situations. However, if applied inappropriately, they will lead to biased decision processes and non-optimal performance. Hoch and Schkade (1996), for example, found that the intuitively appealing anchoring and adjustment heuristic may perform well in highly predictable environments, but that it performs poorly in less predictable environments. Weber and Coskunoglu (1990) note that heuristic processing styles can become so habitual or automatic that they will be applied even in situations where it would be preferable to use more formal or optimal procedures and where the use of heuristics could lead to serious biases.

Summarizing, we have thus argued that complexity in the decision environment enhances the chances of the appearance and the magnitude of biased information acquisition and processing processes. Therefore, we propose:

> *P5*: Higher perceived complexity leads to more biased decision-making processes.

Decisions are a function of decision-makers' cognitive make-up (Henderson and Nutt, 1982). Witkin *et al.* (1971, p. 3) define cognitive styles as "the characteristic, self-consistent modes of functioning which individuals show in their perceptual and intellectual activities." Cognitive style forms a continuum with the two opposite types of decision-makers at the extremes: high-analytical and low-analytical. High-analytical decision-makers tend to reduce problems to a core set of underlying causal relationships. All effort is directed toward detecting those relationships and manipulating the decision variables in such a manner that some "optimal" equilibrium is reached with respect to the objectives. Low-analytical decision-makers tend to look for workable solutions to total problem situations. They search for analogies with familiar, solved problems (Huysmans, 1970).

Since high-analytical decision-makers are able to "see the wood for the trees" (O'Keefe, 1989) and also prefer dealing with numbers (Viswanathan, 1993), decision-making tasks in which decision-makers have to deal with a large pile of numerical marketing information favor high-analytical decision-makers. Research by Lusk and Kersnick (1979), Benbasat and Dexter (1982; 1985) and Cole and Gaeth (1990) has shown that high-analyticals perform better because of the way they structure and solve problems.

From the nature of the cognitive style construct, we infer that low-analytical decision-makers will be more susceptible to the use of heuristics than high-analyticals. van Bruggen *et al.* (1998a,b) indeed found low-analytical decision-makers to be more susceptible to applying the anchoring and adjustment heuristic. Low-analytical decision-makers are also often referred to as "heuristics" (Henderson and Nutt, 1982) and their reasoning behavior as "heuristic reasoning" (Huysmans, 1970). We expect that decision-makers with a more analytical decision style will less easily lapse into the use of heuristics. Therefore, we propose:

P6: More analytical capabilities weaken the relationship between perceived complexity and decision biases.

Developments in information technology and the generation of more marketing data are thus expected to affect the decision-making performance of marketers in two ways. On the one hand, more data are expected to have a beneficial effect, because, potentially, they will lead to greater marketing insights. On the other hand, more information will make the decision environment more complex, thereby stimulating biased decision processes. This will negatively affect the quality of decision making. Combining these propositions leads to:

P7: Decision performance is positively affected by potential market insight and negatively by decision biases.

Managerial judgment is expected to reinforce these effects, both by stimulating the conversion of data into insights and by stimulating the incidence of decision biases. Whether increased amounts of marketing data will have a positive or a negative net effect on managerial performance will depend on the extent to which the data lead to more insights, relative to the extent to which they cause biased decision-making processes. The use of marketing management support systems is proposed to moderate these two types of effects.

Marketing management support systems

Advances in information technology have a second type of impact on marketing management. They not only lead to the availability of large amounts of marketing data. Over the years sophisticated tools have also become available to support marketers. These tools result from developments in both information technology and marketing science. They support decision-makers by making them benefit from the availability of data. We label these tools marketing management support systems (Wierenga and van Bruggen, 1997). Marketing management support systems (MMSS) can be described in terms of their components, as devices that combine:

(1) information technology;

(2) analytical capabilities;

(3) marketing data; and

(4) marketing knowledge.

These components are made available to one or more marketing decision-maker(s) with the objective of improving the quality of marketing management (Wierenga and van Bruggen, 1997). The concept of marketing management support systems forms a generic expression for a variety of systems that have appeared over the last four decades (see Wierenga and van Bruggen (1997) for a more elaborate overview and description of these systems).

Marketing information systems (MKIS) started to appear in the middle of the 1960s and facilitate the storage and retrieval of quantitative data and their transformation into information by applying statistical analyses. Marketing decision support systems (MDSS) appeared in the late 1970s. Marketing decision support systems also recognize the value of managerial judgments by advocating an intensive interaction between the manager and the MDSS in arriving at decisions. Next to a database these systems contain marketing models (MM). Marketing models marked the start of the use of computers for marketing decision making in the early 1960s. They provide a systematic and consistent mathematical relationship between marketing variables and aim at finding optimal solutions to marketing problems. Whereas systems developed before the mid-1980s focused on the manipulation of quantitative data, marketing expert systems (MES) center on manipulating qualitative marketing knowledge that has been captured from human experts. Marketing knowledge-based systems (MKBS), appearing for the first time around 1990, obtain their (qualitative) knowledge from a variety of sources (i.e. including experts) and these systems support reasoning about problems by marketers. Finally, marketing neural nets (MNN), systems that have become available only recently, are modeled according to the way humans process information. These systems can be helpful in finding patterns in large databases when no theory about relationships is available.

The most important goal of marketing management support systems is that they improve the quality of marketing management (decision making). We distinguish three possible mechanisms for such effects. First, MMSS can improve the transformation of marketing data into potential market insight:

> *P8*: Marketing management support systems strengthen the relationship between marketing data and potential market insight.

Second, MMSS can organize and process data in such a way that they produce less complexity:

> *P9*: Marketing management support systems weaken the relationship between marketing data and perceived complexity.

Third, MMSS can reduce the biasing effect of complexity of the decision environment:

P10: Marketing management support systems weaken the relationship between perceived complexity and decision biases.

The extent to which MMSS have one of these three effects depends on the specific type of system. In Figure 2 the extent to which specific types of marketing management support systems are proposed to have the three effects is summarized. Each of these effects is elaborated upon below.

Reducing complexity and developing insights

Blattberg *et al.* (1994) have introduced the concept of the information value chain. This chain contains five successive elements. Each stage adds value to the data. The five elements of the chain are:

(1) data collection and transmission;

(2) data management;

(3) data interpretation;

(4) models; and

(5) decision support systems.

Each of these five elements adds value to the collected data leading to a higher information value (Simpson and Prusak, 1995) and more potential market insight. After data have become available and are organized in an MKIS, systems like a (diagnosing) MKBS and a MES are useful for data interpretation and thus the conversion of marketing data into marketing information.

	Developing insight (MMSS insight)	Reducing complexity (MMSS Red. compl.)	Debiasing (MMSS de-biasing)
MKIS	++	++	
MDSS	++	+	+
MM			++
MKBS/ MES	++		+
MNN	++		

Figure 2. The effects of marketing management support systems

Conditions that call for action will be identified, relationships between variables can be investigated, and diagnoses will be carried out. Next, marketing decision support systems can be developed to capture relationships between marketing variables. Models can process and summarize massive databases and can identify empirical regularities not observable to the human eye (Blattberg and Hoch, 1990; Hoch, 1994). Marketing neural nets can also be helpful for this purpose. Finally, the results of data interpretation and modeling can be the input for marketing decision support systems and (predictive) marketing knowledge based systems. Marketers can use these MDSS, MKBS, or MES in their decision-making activities.

De-biasing effects

The third type of effects of MMSS are their de-biasing effects. Several studies have investigated these effects. Hoch and Schkade (1996) found that, in forecasting tasks, to arrive at a forecast, decision-makers often search their experience for similar situations and then make small adjustments to this previous situation. Their research shows that this strategy performs reasonably well in highly predictable environments but performs poorly in less predictable environments. Results from an experiment show that providing decision-makers with a simple linear model in combination with a computerized database of historical cases improves performance significantly.

In a laboratory experiment using the MARKSTRAT simulation, van Bruggen *et al.* (1998a) found that in a complex decision environment the use of a marketing decision support system makes decision-makers less susceptible to applying the anchoring and adjustment heuristic for making marketing-mix decisions.

More generally Blattberg and Hoch (1990) and Hoch (1994) mention that, compared with experts, models are strong because:

- experts are subject to decision biases of perception and evaluation, where models are not;
- experts often suffer from overconfidence and may be influenced by politics, where models take base rates into account and are immune to social pressures for consensus;
- experts can get tired, bored and emotional, while models do not;
- experts do not consistently integrate evidence from one occasion to another, while models weight this evidence optimally.

The strengths of models extend to the use of systems like MDSS, MES, and MKBS as well. All of these systems are computer-based and will derive information from data and develop suggestions for decisions based on a systematical analysis of these data. Such a systematical analysis will thus not be affected by decision biases, overconfidence, fatigue or inconsistencies. Therefore, all these systems will have a de-biasing effect.

The effects of managerial judgment and marketing management support systems

Summarizing, we distinguish three ways in which managerial judgment (expertise and analytical capabilities) and marketing management support systems moderate the effects of marketing data on decision performance. First, they will affect the transformation of marketing data into potential market insight. Second, they will affect the extent to which more data increase the level of perceived complexity. Third, managerial judgment (i.e. analytical capabilities) and marketing management support systems will affect the extent to which perceived complexity leads to biased decision processes.

The powerful triangle

The data that are collected nowadays offer enormous opportunities for a systematical analysis and preparation of marketing policies. Prior to the availability of all these data, marketing was usually considered to be an art where especially the creativity of the marketer was an important asset (Ing and Mitchell, 1994). Although creativity is still a key-asset of marketers, decision-makers now can and should also benefit from the availability of more and better data by incorporating these data into their decision processes (Blattberg and Hoch, 1990). However, in processing information, decision-makers show several cognitive limitations. Increasing amounts of data thus have both benefits and costs.

The series of propositions developed in this paper makes it possible to systematically analyze the effects of the increasing amounts of data that have become available to marketers on decision performance. We can determine under which conditions (i.e. characteristics of decision-makers and characteristics of the MMSS) it is advisable to provide marketers with more data and under which conditions it is not.

Think, for example, of the situation of a marketer in an FMCG company who has to decide whether he should buy more data or not (for example, buy weekly instead of monthly Nielsen data). If such a marketer will be provided with more data, this does not automatically lead to better decisions. It can be argued that, if the marketer has little expertise and hardly any analytical skills, he will have difficulty in gaining any additional market insights from these data. Moreover, the data explosion might stimulate him to lapse into the inappropriate use of heuristics, because the large amounts of data will cause him to perceive the environment in which he is operating as complex. This may then lead to a situation in which more marketing data will actually have a negative impact on decision performance. Providing such a decision-maker with an MMSS (e.g. an MKIS) that supports him with creating insight in the market will improve the overall decision performance. This is because the marketer will obtain more market insights, which will positively affect decision performance.

Another example concerns a marketer with a lot of expertise and well-developed analytical skills. Such a marketer, initially, will not suffer from more data. In first instance more data will improve his decision performance, because he will be able to translate these data into market insights. However, a point exists where the decision biases caused by additional data outweigh the market insights that result from these data. Beyond this point additional data will have a negative impact. Providing such a marketer with an MMSS that helps generating insights from the data (e.g. an MKIS) will be effective. It can lead to a situation where the marketer can benefit more from additional data and does not suffer as quickly from the data explosion. Furthermore, the negative impact of the data explosion beyond the "optimal data quantity" point will not be as strong as it would be in an unaided situation or in a situation without an MMSS that stimulates the transformation of insights from data.

A marketer with expertise, analytical capabilities and with an MMSS that helps generating insights will be able to benefit from additional data. However, for such a marketer at a certain point more data will cause decision biases that will negatively affect decision performance. In such a situation a system that helps de-biasing decision processes will be very helpful. De-biasing the decision processes will decrease the costs of more marketing data. A de-biasing system can thus lead to a situation in which marketers will be able to benefit from large quantities of data, because the benefits of more data (market insight) will outweigh their costs (decision biases). This leads to a positive relationship between marketing data and decision performance.

Discussion

In this paper we have analyzed the impact of the availability of increasing amounts of data (both more detailed data and data on more variables) on decision-making performance. We conclude that more data will not unconditionally lead to better decisions. Our analysis shows that the data explosion is especially beneficial for marketers who are able to derive insights from these data and who are not vulnerable to decision biases. However, marketers without these capacities can also benefit from more data if they are equipped with the right tools. Marketing management support systems can be effective both by reinforcing strengths of marketers (e.g. creativity, domain knowledge, flexibility and so on) and by compensating for their weaknesses (e.g. cognitive limitations). Therefore, we propose that by using the right type(s) of marketing management support system(s) marketers can benefit from the increasing amounts of data.

By means of the series of propositions developed in this paper one may analyze the effects of providing marketers with specific types of MMSS. This way our reasoning can be used to determine which type of MMSS would be most effective in a specific decision situation. Such a decision situation can be characterized by the data availability, the decision-maker's expertise/experience and his/her analytical capabilities. The last construct can, for example, be measured by means of the Embedded Figures Test (Witkin *et al.*, 1971). One could imagine situations in which providing the decision-maker with more marketing data might have negative effects, because the negative effects of complexity outweigh the positive effects of increased marketing insights. This could be the case, if, for example, the marketer is not good at generating marketing insights from marketing data and does suffer from the complexity caused by the data. In such a situation the usefulness of specific types of MMSS (e.g. MKIS, MDSS or MES) can be determined: that is, should such a system especially focus on reducing complexity and/or de-biasing decision processes or should it especially help to generate insights?

The propositions are relatively simple and alternative formulations are well imaginable. However, we think that they offer a conceptually plausible synthesis of research findings and a starting-point for further research. The proposed relationships can of course be criticized. It would be interesting to study how the relationship between the quantity of marketing data and the marketing insights generated from these data looks and to what extent the form of this relationship would be different for different types of MMSS. Similarly, the relationships between quantity of marketing data and perceived complexity, and perceived complexity and the appearance of decision biases, would be an interesting subject for research. This type of research could be carried out using an experimental approach.

Furthermore, the propositions in their current form contain only a limited number of variables. In the first instance, the relevant dimensions of the variables should be determined. Indicators, for example, of the marketer's capacity to derive insights from data, to organize data and their vulnerability to biases should be developed and incorporated. The same should be done for variables that more specifically characterize marketing management support systems. Extending the propositions with variables that characterize the environment in which the marketer is operating will also be useful.

Currently we propose only the main effects of the important constructs. Adding higher-order interaction effects (Eierman *et al.*, 1995) between, for example, the managerial judgment and the MMSS construct might be a useful extension. It is imaginable that a specific type of MMSS will be more effective in the hands of a marketer with certain characteristics (e.g. analytical skills) than in the hands of another marketer who does not possess these skills.

In our analysis we have assumed a rather static situation, in which a marketer has to decide whether it is advisable or not to collect more data. However, the process that we described will be dynamic in the sense that, for example, marketers' expertise will develop itself by analyzing data, making decisions and receiving feedback. This implies that the relationships between the constructs will change over time and that the effect of additional marketing data will also change. Although the parameter values might change, the basic structure of our model itself will not change over time.

Finally, elements of managerial judgment like expertise may not only directly affect managerial performance, but may also stimulate the development and further improvement of marketing management support systems. We think that marketing management support systems should not replace managerial judgment but that these systems do benefit from, for example, a marketer's expertise by incorporating (parts of) it. Marketing expert systems and marketing knowledge-based systems are based on this idea, which further enhances the effectiveness of MMSS.

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About the authors

Gerrit H. van Bruggen

Gerrit H. van Bruggen is Professor of Marketing at the Rotterdam School of Management, Erasmus University Rotterdam. In his research he studies the impact of information technology on marketing. Together with Berend Wierenga he recently published a book on *Marketing Management Support Systems* (Kluwer Academic Publishers). His research publications have appeared in journals such as *Management Science*, *Marketing Science*, *Journal of Marketing*, *International Journal of Research in Marketing*, *Interfaces* and *MIS Quarterly*.

Ale Smidts

Ale Smidts is Professor of Marketing Research at the Rotterdam School of Management, Erasmus University, The Netherlands. His research interests include managerial decision making; risk attitudes and risk perception; and topics in services marketing such as the psychology of (waiting) time, the impact of the physical environment (servicescape) on consumer behavior and the management of customer satisfaction and loyalty. His research has appeared in journals such as *Management Science*, *International Journal of Research in Marketing* and *The Academy of Management Journal*.

Berend Wierenga

Berend Wierenga is Professor of Marketing at the Rotterdam School of Management, Erasmus University, Rotterdam and Scientific Director of ERIM (Erasmus Research Institute of Management). Most of his research is in the area of Marketing Management Support Systems. Together with Gerrit van Bruggen, he recently published a book on this subject (*Marketing Management Support Systems: Principles, Tools, and Implementation* (Kluwer Academic Publishers)). He has published recently on the same topic in journals such as *International Journal of Research in Marketing*, *Journal of Marketing*, *Management Science*, *Marketing Science*, *Communications of the ACM* and *Management Information Systems Quarterly*.

Hugh N. Wilson

Hugh Wilson is a Visiting Fellow and Director of the Centre for e-Marketing at Cranfield School of Management. After a mathematics degree at Oxford University and a postgraduate computer science degree at Cambridge University, he spent 13 years in the computing industry, before gaining a prize-winning PhD from Cranfield University on decision support systems for marketing planning. He has published a number of books and management reports, including *e-Marketing: Improving Marketing Effectiveness in a Digital World* (*Financial Times*/Prentice-Hall, 1999) with Malcolm McDonald.

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