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DSS Effectiveness in Marketing Resource Allocation Decisions: Reality vs. Perception

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We study the process by which model-based decision support systems (DSSs) influence managerial decision making in the context of marketing budgeting and resource allocation. We focus on identifying *whether* and *how* DSSs influence the decision process (e.g., cognitive effort deployed, discussion quality, and decision alternatives considered) and, as a result, *how* these DSSs influence decision outcomes (e.g., profit and satisfaction both with the decision process and the outcome). We study two specific marketing resource allocation decisions in a laboratory context: sales effort allocation and customer targeting. We find that decision makers who use high-quality, model-based DSSs make objectively better decisions than do decision makers who only have access to a generic decision tool (Microsoft Excel). However, their subjective evaluations (perceptions) of both their decisions and the processes that lead to those decisions do not necessarily improve as a result of DSS use. And expert judges, serving as surrogates for top management, have a difficult time assessing the objective quality of those decisions.

Our results suggest that what managers get from a high-quality DSS may be substantially better than what they see. To increase the inclination for managerial adoption and use of DSS, we must get users to "see" the benefits of using a DSS. Our results also suggest two ways to bridge the perception-reality gap: (1) improve the perceived value of the decision process by designing DSSs both to encourage discussion (e.g., by providing explanation and support for alternative recommendations) as well as to reduce the perceived complexity of the problem so that managers invest more cognitive effort in exploring additional options and (2) provide feedback on the likely market/business outcomes of various decision options.

Key words: DSS; marketing models; decision quality; decision process; resource allocation
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Introduction

The determination and allocation of a budget (of time or resources, financial or otherwise) is a pervasive human activity. For example, we must all determine our budget for food, necessities, and leisure activities and allocate those budgets within those categories. We must also determine how much of our time we will work each week and how much of our remaining time we will spend with our children, surfing the Internet, watching television, and the like. Firms continually face such resource allocation challenges. They must determine how much to spend on new product development and how to allocate those funds across projects and time. Charitable organizations must determine what their development budget should be and what past donors or prospects to target. Manufacturers must decide how much plant capacity to invest in and where that capacity should be placed.

The determination of the budget and the allocation of that budget are tasks that are straightforward to define conceptually and mathematically, but not at all that simple for humans to perform "optimally" without some decision aid. Indeed, such decisions helped form Simon's (1955) view of satisficing behavior, where he states that "there is a complete lack of evidence that in actual human choice situations these computations can be or are in fact performed" (p. 105). It is perhaps not surprising, therefore, that a search on Google on June 14, 2004, for "resource allocation" and "software" turned up nearly 390,000 links. While it would seem then, that in an area of such importance, we would have substantial and definitive evidence about the benefits and costs of using decision support aids for resource allocation in various application domains, such is not the case. For example, Agarwal et al. (1992) describe critical elements missing in systems to help support the choice of management information system (MIS) projects under resource constraints, a resource allocation task; Muckstadt et al. (2001) describe at least five key elements that they claim are missing in the design of systems to support resource allocation decisions in a supply chain. Indeed, there appears to be only modest evidence to support the belief that model-based DSSs can help improve business decisions of any sort (Sharda et al. 1988, Benbasat and Nault 1990, Todd and Benbasat 1999).

We focus here on one domain for specificity: organizational resource allocation decisions in marketing: how large the marketing budget should be (e.g., for advertising, sales promotion, and sales force effort) and how that budget should be allocated over geographies, products, market segments, and time. And while there is some evidence of the effectiveness of model-based systems to support such decisions, the adoption rate of such systems by firms remains far below potential (Wierenga and Van Bruggen 2000). A study by Accenture (2001) points out that more than two-thirds of the more than $1 trillion spent by the Global 1000 on marketing is allocated without any return on investment (ROI) justification, much less supported by a DSS.

Is the apparent low level of adoption of decision support models in marketing because of their inherent lack of value, because their value (perceived or actual) is not sufficiently high for the adopting organization to incur the costs that the adopting individuals may be forced to bear, or because of some combination of these factors? We study these issues by exploring *how* DSSs influence the decision process (e.g., cognitive effort deployed, discussion quality, and decision alternatives considered) and, as a result, *how* these DSSs influence decision outcomes (e.g., profit and satisfaction both with the process and the outcome). We study two specific marketing resource allocation decisions, i.e., sales effort allocation, and customer targeting.

We define a *DSS* as a packaged software application that uses analytical models to transform business data into numerical and graphical reports to help users make business decisions more easily and effectively. In our conceptualization of DSSs the presence of built-in analytical decision models is essential, distinguishing a DSS from a more general-purpose tool like Excel. Also, DSSs for resource allocation differ on analytical model sophistication, ranging from relatively simple descriptive response models to sophisticated normative optimization models providing problem-specific recommendations. In this study, we investigate the effects of two quite sophisticated DSSs for resource allocation.

There have been several studies on the effects and effectiveness of marketing DSSs, including DSSs designed for resource allocation.[1] Most have focused primarily on exploring *whether* the use of a DSS improves the performance of decision makers as measured by decision quality (typically based on outcome variables such as sales, profit, or market share computed endogenously from the model) or by decision makers' satisfaction and confidence in the results of using the DSS. Only a few studies have examined how a DSS affects the decision process, and the few that have, have not investigated how the DSS influences both the process and the outcomes.

The studies report mixed results regarding DSS effects on outcomes. Most studies in the marketing literature report that DSSs improve marketing resource allocation decisions, with the notable exception of the study by Chakravarti et al. (1979), which concluded that the use of a DSS had a detrimental effect on decision quality. However, the broader DSS research reports mixed findings in laboratory studies on the effects of DSSs on decision outcomes (see Sharda et al.

[1] See, e.g., Fudge and Lodish 1977; Chakravarti et al. 1979; McIntyre 1982; Lodish et al. 1988; Gensch et al. 1990; Hoch and Schkade 1996; Van Bruggen et al. 1996, 1998; Eisenstein and Lodish (2002) provide a review.

1988, Benbasat and Nault 1990). Of the 11 studies that Sharda et al. (1988) reviewed, 6 showed improved performance because of DSS use, 4 showed no difference, and in 1 study performance actually decreased for DSS users. We note three issues with respect to the past studies.

(1) Most studies have not tracked the decision processes associated with DSS use.

(2) It is possible that DSS can improve objective decision outcomes without having a positive effect on the subjective evaluations of these decisions and vice versa, and it would be useful to understand the separate nature of these two effects.

(3) Field studies have used DSSs to address real managerial problems, but have lacked effective experimental control (e.g., Fudge and Lodish 1977), making it difficult to demarcate the drivers of DSS performance, while lab studies have imposed sound experimental controls, but have addressed relatively simple and contrived problems.

We designed our research to balance the benefits of experimental control (internal validity) with those of real-world applicability (external validity) by conducting a laboratory study where we used field-tested DSSs and real-world cases, for which actual outcomes are both known and have been reported in the academic literature. In view of the limitations of past studies, we designed our research to incorporate the following three features.

(1) *Broad assessment of DSS impact*. We incorporate objective measures, exogenous expert judgments, *and* subjective perceptions of DSS impact, including both multiple dependent (outcome) and mediating (process) variables. We evaluate whether a DSS influences outcomes, and also study *how* that influence is moderated by changes in the decision process.

(2) *Two different DSSs*. We study the effects of two DSSs that have different foci, although both address resource allocation problems: customer targeting for ABB Electric and sales force allocation for Syntex Labs (described in subsequent sections). Having two different DSSs should allow us to more readily identify results/relationships that are both common and unique across these two types of resource allocation models.

(3) *Realistic study context*. Unlike most previous studies, we do not compare a DSS versus a non-DSS treatment, an unrealistic comparison. Instead, subjects in our non-DSS condition (which we will refer to as the Excel-only condition throughout for clarity) have access to and can manipulate (through Excel) the same data as the DSS subjects, as is the case in natural settings. Excel is a DSS generator that enables our subjects to do estimation and optimization tasks, both of which are useful for addressing the resource allocation problems faced by our subjects. However, Excel does not automatically enable people to develop problem representations to fully exploit the available information. Our DSSs, unlike a more general-purpose tool like Excel, build in the DSS developers' expertise in the design, potentially helping users to both better understand how to represent the problem as well as how to develop specific, defensible recommendations.

The theoretical underpinnings of our study rest on the cost-benefit framework of cognition (Payne et al. 1993), applied to the field of decision support by Todd and Benbasat (1999), and on the *fit-appropriation model* (FAM) developed to understand the effects of group support systems (Dennis et al. 2001). From these theories, we postulate that DSSs that have task-technology fit (i.e., are of high quality) can improve decision quality/accuracy and/or improve decision outcomes. However, these theories also suggest that decision makers prefer less effort to more effort. Blending these theoretical perspectives, we develop hypotheses about the kinds of effects the DSSs will have on marketing resource allocation decisions.

Our results show that decision makers with access to high-quality, model-based DSSs make objectively better decisions than do those with access only to Excel. However, subjective evaluations of both the decisions made and the decision processes that lead to those decisions, do not necessarily improve as a result of DSS use. In particular, even expert judges have difficulty assessing the objective quality of those decisions. We also find that DSSs can lead to better objective decision outcomes without seeming to affect some aspects of the decision process, such as the number of decision alternatives considered. However, to improve subjective evaluations of decision quality, a necessary precondition for DSS adoption, the decision process must be influenced in such a way that it is viewed favorably.

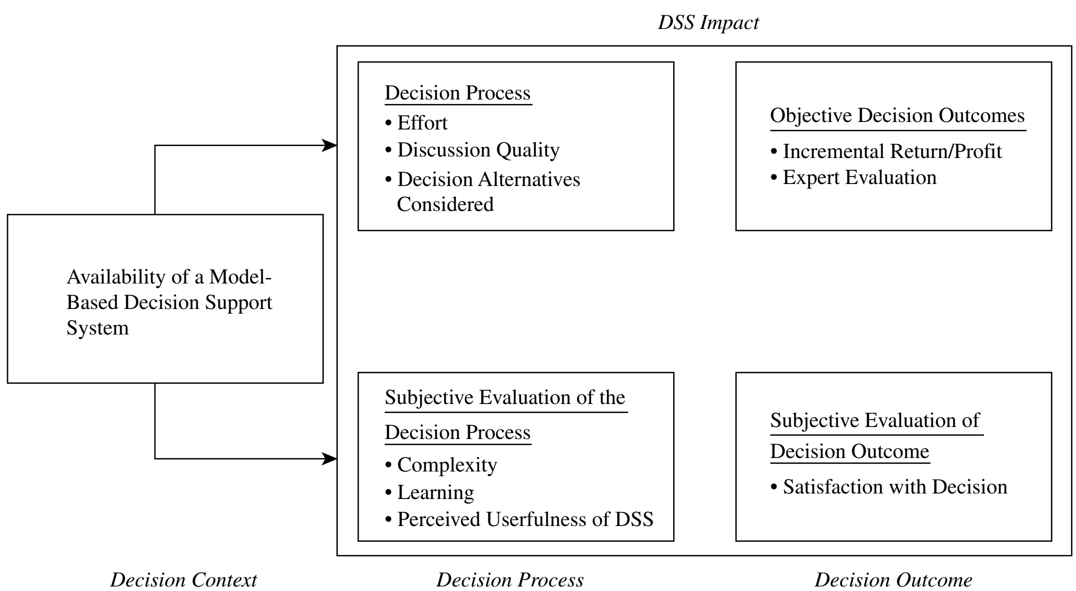
The Impact of Model-Based DSS: Hypothesis Development

To assess *whether* and *how* a DSS leads to different decision outcomes, we must distinguish the effects of a DSS on various impact measures and separate the effects of a DSS on the decision process from its effects on decision outcomes. DeLone and McLean (1992), seeking a measure of general information systems (IS) impact or success, report "rather than finding none, there are nearly as many measures as there are studies" (p. 61). They identify several categories of IS impact and make an important distinction between the effect of the IS on the individual and the effect on the organization. The individual-level impact of an IS is closely related to the user's perceived performance given IS use, but the impact can also involve providing a user with a better understanding of the decision problem or changing the user's perception of the usefulness of the IS. The organizational impact of an IS relates to its effect on organizational performance, which can be measured in terms of firm profit, sales, or related performance metrics, an area in need of research (DeLone and McLean 1992). This taxonomy of IS success measures applies to the DSSs we study: We address both the individual and the organizational impact of DSSs and distinguish two categories of impact variables—DSS impact on decision *process* and their impact on decision *outcomes*. Within both impact categories, we distinguish between objective outcomes and subjective evaluations. Combining these two dimensions, we study the impact of DSSs on four groups of variables: (1) the characteristics of the team decision process, (2) the (individual) subjective evaluation of the team decision process, (3) objective decision outcomes for the team, and (4) the (individual) subjective evaluation of the decision outcomes (see Figure 1). We investigate the impact of DSS on specific measures within each of these four classes of variables.

Decisions emerge from an underlying decision process, which can be characterized by the amount of cognitive effort that people devote to problem solving, the quality of the discussions they have during the decision process, the decision alternatives they consider, and so on. Both the decision outcomes and the decision process, in turn, will be influenced by the context in which decision makers operate. This context can be described by the characteristics of the decision environment, the characteristics of the decision makers who must resolve problems, and the characteristics of the available DSSs, especially how appropriate they are for the tasks faced by the decision makers.

A priori, we can expect decision models to have a positive effect on decision outcomes for several

Figure 1 Research Framework



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 timeframes, they use heuristic approaches to solve problems, which trigger various cognitive biases that could diminish decision quality. An example heuristic is *anchoring and adjustment*. Decision makers who apply this heuristic start from an initial "anchor" point and adjust it to arrive at a decision. When there are strong anchors, adjustments from an anchor point tend to be suboptimal (Slovic and Lichtenstein 1971, Mowen and Gaeth 1992). Many techniques have been proposed in the literature to "debias" the decision-making process, including task simplification, providing training and feedback to decision makers, and providing simulators to generate multiple alternative explanations (Croskerry 2003). A DSS can potentially be a debiasing tool to reduce several types of bias (Arnott 2002).

In resource allocation tasks, DSSs can help managers cope with large amounts of information and integrate that information in a consistent way (Dawes 1979). In particular, a DSS can help managers choose good resource allocation 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. At the same time, a DSS can underweight important idiosyncratic elements (e.g., the strategic desirability of an option) relevant to a particular resource allocation problem. Given these advantages and limitations of DSSs, it is perhaps not surprising that several researchers have demonstrated that a combination of a DSS and human decision making outperforms unaided decision makers (Blattberg and Hoch 1990, Hoch 1994, Hoch and Schkade 1996). The main explanation for this finding is that DSSs cause changes in the (imperfect) processes by which decisions are made (Silver 1990). 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).

However, the mere availability or use of DSSs will not automatically lead to better decisions because decision makers make effort-accuracy tradeoffs (Payne et al. 1993) in their decision processes, and these trade-offs affect the quality of the decision outcomes. The literature suggests that effort is the most important factor influencing strategy selection (Todd and Benbasat 1999). If a DSS enables a higher quality decision process with no more effort than the current process, that higher quality DSS process is more likely to be adopted. However, if a DSS allows the decision maker's existing decision process to be executed with less effort, then the decision quality may not improve. It is generally easier for decision makers to assess efficiency gains (e.g., savings in cognitive effort) from DSS use than it is for them to assess decision-quality improvements, especially if they are inexperienced and unfamiliar with the DSS. Only if a DSS is intrinsically of high quality and makes it easy to deploy higher quality decision processes will DSS use improve both objective decision outcomes and decision efficiency. However, if users do not recognize the intrinsic quality of the DSS or the value of the outcomes it helps generate, they may not be satisfied.

The fit-appropriation model (FAM) (Dennis et al. 2001) proposes that the effects of (group) DSSs are influenced 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, facilitating, routinizing, 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 significantly even when task-technology fit is high. That is, the effect of task-technology fit on performance will be moderated by appropriation support. Appropriation itself, in turn, is affected by the fit (a good fit is more likely to lead to faithful appropriation). 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 DSSs can be expected to improve objective decision outcomes if they show a sufficiently high level of task-technology fit. Given decision makers' natural tendency to prefer effort reduction, and the fact that merely following the recommendation of a high-quality DSS offers both low effort and high decision quality, we can expect high-quality DSSs to improve objective outcomes (incremental return/profit). For our study, we selected DSSs that have *high* task-technology fit, a necessary condition for improving objective decision performance. We also chose the level of appropriation support to reflect the conditions under which resource allocation software is typically used by marketing managers, as few companies today maintain a large analytic staff to provide extensive support for managers. Rather they operate in environments characterized by *moderate* appropriation support for software (e.g., telephone/web support, remote diagnostics, and so on).

We investigate the effects of the availability of model-based DSSs relative to the use of the general purpose decision tool, Microsoft Excel. Excel is a DSS generator that enables estimation and optimization, both of which are useful for the tasks faced by our subjects. However, Excel does not help users with problem representation (i.e., what to estimate and how, or what to optimize and how). Without the appropriate problem representation, the available data may not be exploited to the fullest. In contrast, our DSSs provide a sort of blueprint, embedding an analytical process for problem formulation and representation that allows the users to more fully exploit the available data. In a sense, Excel is just a toolkit whereas our DSSs are toolkits that come with a blueprint, permitting users to exploit the toolkit most effectively. Thus, although Excel is less restrictive than our DSSs, it offers no guidance to fully exploit its capabilities in a specific problem context. Therefore, the Excel-only aid has a lower task-technology fit than the two DSSs used in the study.

The two DSSs in our study are similar to each other in that they both support resource allocation decisions, and both show a high level of task-technology fit and moderate appropriation support. However, they differ in important ways: the DSS for ABB is nondirective (i.e., it gives no feedback, nor does it generate specific recommendations) whereas the Syntex DSS provides both a specific recommendation and a projected profit impact of that recommendation, relative to the current allocation. Goodman (1998) and Wigton et al. (1986) show that such feedback can play both an informational role (promoting knowledge acquisition) as well as a motivational role (providing a reward cue for increasing cognitive effort investment). In the framework of Balzer et al. (1989), user interactions with the Syntex DSS (but not with the ABB DSS) provide "cognitive feedback," linking the task with the environmental performance measures. Note that the Syntex DSS allows users to conduct "what-if" analyses, experimenting with different constraints and observing their impact on expected profits. The ABB DSS only offers users additional information in terms of computed probabilities, but does not include options to explicitly encourage users to experiment with or analyze multiple scenarios, as was the case with the Syntex DSS. Even though both DSS have moderate levels of appropriation support (e.g., no direct training), Syntex provides more appropriation support than ABB, and could lead to higher effort deployment, which in turn could lead to better outcomes. However, we do not postulate these differences as formal hypotheses.

Based on the above reasoning, we propose the following hypotheses about the impact that the use of *high-quality* DSS will have on various measures of performance.[2]

Hypothesis 1. *Model-based DSSs will improve objective decision outcomes relative to the Excel-only tool.*

Hypothesis 1a. *DSSs will generate more incremental returns/profits relative to the Excel-only tool.*

Hypothesis 1b. *DSSs will result in more favorable experts' evaluation of the decisions relative to the Excel-only tool.*

Because we have a moderate level of appropriation support, we posit the following.

Hypothesis 2. *DSSs will have no effect on the subjective evaluation of the decision outcomes relative to the Excel-only tool.*

Hypothesis 2a. *DSSs will have no differential effects on decision satisfaction relative to the Excel-only tool.*

[2] In these hypotheses, the term "use of DSSs" implies (1) high task-technology fit, (2) a moderate level of appropriation, and (3) use for resource allocation decisions.

With only moderate appropriation support, it would be difficult for decision makers to judge the value of the available DSS, and therefore they would not be able to fully assess how their decision-making efforts improve decision quality. Therefore, decision makers are more likely to reduce effort at the expense of decision accuracy. It is also possible that the availability of a model to facilitate discussions could lead decision makers to (incorrectly) pursue quick consensus when, in fact, it may be in their best interest to generate more alternatives, and evaluate them more autonomously (Miranda and Saunders 1995). In view of the above arguments, we expect less effort, but more focused and higher quality discussions (because of the high-quality DSS), which also means that fewer decision alternatives will be generated or evaluated carefully. We, therefore, hypothesize the following.

Hypothesis 3. *DSSs will have mixed effects on the decision process.*

Hypothesis 3a. *DSSs will lead to less effort devoted to problem solving than the Excel-only tool.*

Hypothesis 3b. *DSSs will enhance the quality of the discussions as compared to the Excel-only tool.*

Hypothesis 3c. *DSSs will lead to fewer decision alternative generated than the Excel-only tool.*

Appropriation support involves training, facilitating, routinizing, or software restrictions to help users incorporate a DSS within their decision-making process. We can expect moderate levels of appropriation support to lead to less intensive decision processes with mixed effects on the subjective evaluation of these processes. On the one hand, if decision makers spend less effort on the task because of the facilitation offered by the DSS, they may not discover the full complexity of the task. On the other hand, they may view the decision problem as complex, and because they do not spend much effort developing a full understanding of the problem, the complexity remains even after DSS use. Given these two countervailing effects, we hypothesize no significant net effect of the DSS on perceived problem complexity. And because decision makers may use the DSS for effort reduction, it may reduce the amount of learning that occurs because of DSS use. Finally, the DSS should help decision makers improve along at least one dimension: lower effort or higher decision quality. Therefore, we expect DSSs will be perceived as being useful.

Hypothesis 4. *DSSs will have mixed effects on the subjective evaluation of the decision process.*

Hypothesis 4a. *DSSs will have no effect on perceived problem complexity relative to the Excel-only tool.*

Hypothesis 4b. *DSSs will lead to less perceived learning relative to the Excel-only tool.*

Hypothesis 4c. *DSSs will be perceived as useful relative to the Excel-only tool.*

Methodology

To test the hypotheses, we applied six criteria to select our methodology. First, we conducted our research in a laboratory setting because we wanted our decision context to be replicable to permit statistical model building and hypothesis testing. Second, our study required a realistic decision context to enhance external validity. Third, we wanted our hypotheses to be testable across DSS designs. Therefore, we included two realistic resource allocation scenarios, which had DSSs associated with them: the ABB Electric case and the Syntex Labs (A) case, both of which received the Edelman Prize from INFORMS as outstanding examples of the practice of management science. Papers describing these models (Gensch et al. 1990, Lodish et al. 1988) include the actual market response to the resource allocation decisions implemented by the respective firms. Therefore, it is possible, ex post, to estimate likely decision effectiveness. Fourth, our subjects should be real decision makers or have had sufficient training in the domain to understand the issues associated with resource allocation decisions. Fifth, subjects should have the background and capability to understand and use spreadsheets and market response models. Sixth, our subjects must not be experts (e.g., analysts) in the use of DSSs, because our hypotheses concern decision making by typical managers.

These criteria lead us to consider business school undergraduates, MBAs, and company executives. Pilot tests with undergraduates showed that they did not have sufficient background to understand the problem context. We were not able to locate a large enough group of executives who were sufficiently homogeneous in background and skill level to meet our needs. Pilot studies with MBA students who had taken core marketing and management science courses showed that such students not only were able to understand both the context (marketing resource allocation) and the approach (spreadsheet tools and response model-based decision support), but were also sufficiently homogenous along other dimensions to make them appropriate subjects.

We adapted software implementations of the ABB and Syntex model from Lilien and Rangaswamy (1998). To mimic the organizational reality and group decision process associated with such decisions in practice, we used two-person teams as the experimental unit. We randomly assigned each team to one of eight experimental conditions to analyze and develop recommendations for both cases. All groups received identical data (described in the cases) in the form of spreadsheets and had the full functionality of Microsoft Excel available to them. The groups differed in (1) whether their spreadsheet included an embedded DSS model that allowed them to analyze the data (if they chose to) using a resource allocation model and (2) the order in which they analyzed the cases—ABB followed by Syntex or Syntex followed by ABB. We briefly describe these two cases and the associated models.

ABB Electric Case. The decision problem was to allocate a supplementary marketing budget to the "top 20" customers (out of 88) to be recommended by the subjects. The data reported how each of these customers rated the four suppliers (including ABB) on criteria such as invoice price, technical specs of the products, availability of spare parts, and so on. Subjects who had access to the DSS were also able to run a multinomial logit analysis to determine the probability of each customer buying from each of the four suppliers. The subjects could then use the results of the model analysis in any way they thought was appropriate (e.g., sort customers according to their probability of purchasing from ABB and construct an index of vulnerability or attractiveness) in identifying the target customers.

To provide a common decision anchor, all subjects were told the company had historically targeted its marketing programs at its largest customers, but that a company consultant had introduced the concept of targeting customers by "switchability." The new idea was to target those customers whose likelihood of purchase indicated that they were "sitting on the fence" with respect to purchasing from ABB (i.e., where ABB was either a narrow first choice or was the second choice by a narrow margin), and pay less attention to those customers who were already either loyal to competitors or were loyal to ABB. Switchability segmentation conflicted with the prior company resource allocation strategy, which was to target purely based on sales potential of the customers, putting more effort on customers with higher sales potential. Figure 2 summarizes the key data as well as the results from running the multinomial logit model (available to groups that had access to the DSS).

Syntex Labs (A) Case. The Syntex case describes the situation that Syntex Labs faced in 1982, when it had 430 sales representatives in the United States and were adding 40 reps per year. The company had 7 different products and the stated management plan was to continue adding 40 reps per year, and to allocate those reps to those 7 products proportionally to the current allocation of representatives. The company was concerned both about the total size of its sales force and the allocation of the sales effort across products, because a relatively new product, Naprosyn, was popular and appeared to be underpromoted relative to the resources allocated to other products. The case describes the concept of a response model and the hiring of a consultant who led a team of Syntex executives through the calibration of that response model. All subjects received data on the current level of effort, the allocation of that sales effort to products, the current sales of these products, the profitability of the products, the current overall profitability of the firm, and the results of the response model calibration session. This latter information—the answer to questions such as "What would the percentage sales of Naprosyn be with a 50% increase in its sales force allocation from (current) 96.8 sales reps to 145.2?" Answer: "26% increase" (Cell I9 in Figure 3)—was provided to the respondents in Excel template format as presented in Cells G9–J15 in Figure 3. The DSS-supported group also had access to an optimization model that generates the recommendations in Columns D and E in Figure 3. That model

Figure 2 ABB DSS—Resource Allocation Model, Giving Purchase Likelihood by Brand for Each Potential Customer

File Edit View Insert Format Tools Data Window Help Model

J20 =

Customer Demographics (Descriptors)

Supplier	Pref. Supplier
A: ABB	18
B: GE	23
C: Westingh.	26
D: McGraw-E.	21
Sum	88

Potential Customer	RFQ Estimated Purchase Vol. ($K	District	Firm Chosen	Consultant Recommended Target A(ABB)	Supplier B	Supplier C	Supplier D
1	$761	1	B	15.3%	82.3%	2.4%	0.0%
2	$627	1	D	0.0%	0.0%	2.6%	97.4%
3	$643	2	A	74.7%	25.3%	0.0%	0.0%
4	$562	3	D	48.8%	39.7%	0.0%	11.5%
5	$469	3	C	2.0%	0.0%	98.0%	0.0%
6	$233	1	B	0.0%	96.8%	3.1%	0.0%
7	$664	3	D	40.5%	7.7%	0.1%	51.8%
8	$767	3	D	0.0%	56.4%	0.0%	43.6%
9	$467	1	D	0.3%	0.0%	1.3%	98.4%

Note. The model-supported groups could run a multinomial logit (MNL) model to obtain the choice probabilities of each supplier for each customer. The Model menu option in the program enables the subjects to access the MNL model and obtain the result above.

Figure 3 Syntex DSS Output—Unconstrained Optimization, Showing What the Model Recommends with No Restrictions on the Amount of Selling Effort

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J17 =

Product Model

Unit Cost of Salesperson $ 63

Segment	Base Selling Effort	Recom-mended Sales Force	Recom-mended Sales Level ($)	Unit Margins (0 - 1)	Base Estimates None	1/2-	1/2+	Sat.
Naprosyn	96.8	321.0	312,419	0.700	0.47	0.68	1.26	1.52
Anaprox	142.4	168.4	40,158	0.550	0.15	0.48	1.20	1.35
Nor135	52.7	70.8	23,514	0.720	0.31	0.63	1.15	1.25
Nor150	24.1	37.1	39,829	0.720	0.45	0.70	1.05	1.10
Lidex	27.3	46.9	42,272	0.530	0.56	0.80	1.11	1.20
Synalar	29.7	30.3	14,670	0.530	0.59	0.76	1.07	1.11
Nasalide	56.8	69.8	13,008	0.520	0.15	0.61	1.46	1.76
Total	429.8	744.4	485,870					

Net Profit = ($000) $218,827 $276,433

Note: 1. All $ figures are in 000's
2. Net profit = Sum (over products) of Product sales * Product margin - # product salespeople * cost/salesperson ($63,000)

Sheet1

Ready

Note 1. Base selling effort = current sales force allocation in number of representatives.
Base sales = expected sales in 1985 with base selling effect.
Unit margin = group profit/unit before allocating sales costs.
Base response estimates = % increase/decrease in sales with noted increase/decrease in selling effort (both relative to "base").
Note 2. The Excel-only group had access only to base selling effort, base sales data and base market response estimates.

allowed subjects to determine the "optimal" (short-term profit maximizing) sales force size and effort allocation, either on an unconstrained basis or under user-specified constraints. Those constraints could be placed either on the total size of the sales force or on individual products. Subjects were given a common decision anchor to allocate any increase in sales effort proportionally to the most recent level of effort allocation, a widely used process in practice.

The ABB DSS and the Syntex DSS differ both in their designs and in respect to the problem context in which each is used. The ABB DSS does not make specific recommendations about which customers to target under various user-selected criteria (the user has to develop those criteria), nor does it provide any expected outcomes associated with a resource allocation decision. In contrast, the Syntex DSS, through a profit optimization tool, makes specific recommendations for the sizes of the sales force and effort allocation, and also provides the resulting level of expected profit (computed from sales response functions). Thus, Syntex is a directive DSS, which provides its users with specific feedback on the expected sales and profit outcomes of alternative resource allocations.

Experimental Procedure. Subjects analyzed both the ABB and the Syntex cases in two-person teams. We systematically manipulated the availability of a DSS as shown below. To address order effects, half the groups did the ABB case first followed by the Syntex case, while the other groups did the reverse. Table 1 summarizes the resulting eight experimental conditions.

Our experimental procedure consisted of the following five steps.

Step 1. *Background and Qualifications*. After entering the lab, each subject completed a pre-experimental questionnaire with questions about demographics (age, gender, and so on), work background, and computer and Excel experience. We used this information to check (post hoc) whether the teams in the various experimental conditions had similar backgrounds and qualifications.

Step 2. *Case* 1. Subjects as a group received their first case and a tutorial illustrating how the related software worked. The tutorials that were given to subjects with the DSS contained additional information about running the DSS. After they had analyzed the case, all groups completed forms summarizing their recommendations and their justifications for those recommendations.

Step 3. *Postanalysis Questionnaire* 1. After completing their recommendation form for the first case, all subjects (individually) completed a postanalysis questionnaire that asked for their subjective evaluations of their case analysis, the associated discussions, their recommendations, and their assessment of the available software.

Step 4. *Case* 2. The same as Step 2, but now for the second case.

Step 5. *Postanalysis Questionnaire* 2. The same as Step 3, but now for the second case.

At the end of the exercise, the subjects were debriefed and asked not to discuss the case with anyone.

Subjects. There were 112 first year MBA students who participated in our study, making 56 groups, with 7 groups per experimental condition. We paid each subject $25 for their (approximately) 3 hours of participation. We told all groups they were eligible to win one of three group prizes, depending on their performance.

Measures. We classify the variables used in the study as (1) experimental factors (independent variables) and the following dependent DSS impact variables: (2) group decision process variables, (3) subjective evaluation of the group decision process variables, (4) objective decision outcome variables, and (5) subjective evaluations of decision outcomes variables. (We also collected information on problem-solving style and computer and Excel efficiency and found no significant differences between experimental groups.) Below, we describe these variables and their measurement.

Table 1 Experimental Conditions

DSS condition	Task order (ABB first, Syntex second)	Task order (Syntex first, ABB second)
No DSS	Group 1	Group 2
DSS followed by No DSS	Group 3	Group 4
No DSS followed by DSS	Group 5	Group 6
DSS	Group 7	Group 8

Experimental Factors. We systematically manipulated the following two experimental factors.

(1) *DSS Availability*. Yes—1 or No—0, for the two DSSs being used; namely, ABB and Syntex. Unobtrusively collected tracking data showed that the decision groups that had the DSSs available always used them.

(2) *Order*. ABB first/Syntex second = 0; Syntex first/ABB second = 1. To control for order effects, we had half the teams start with the ABB case and other half start with the Syntex case in a manner that made order independent of the two experimental factors overall.

DSS Impact. In Tables 2a–d, we summarize the process and outcome variables that we used to measure DSS impact. Wherever feasible, as noted in the tables, we used or adapted scales from previous research, although for several constructs, as indicated in Tables 2b–d, we had to develop new measures because well-tested scales either did not exist or were inappropriate for our context. We used LISREL 8.3 (Jöreskög and Sörbom 1993) to assess the quality of the seven subjectively measured multiple-item measurement instruments (e.g., subjective evaluations of effort, discussion quality, decision alternatives considered, complexity, learning, perceived usefulness of the DSS, and satisfaction with the decision). We specified one confirmatory factor analysis model. The chi square for this model is 171.09 ($p = 0.81$). The comparative fit index is 1, above the generally accepted level of 0.90. The value of the standardized root mean square residual is 0.058. All factor loadings are highly significant (minimum t-value is 4.40, $p < 0.001$, and most t-values are above 10) and larger than 0.50 (except for one loading, which was 0.35). These findings support the convergent validity of the items. The correlations between the seven constructs are significantly different from unity, which supports their discriminant validity. In view of the small sample size of our data set, we also developed confirmatory factor models separately for each group of impact measures (see Figure 1), i.e., for decision process, subjective evaluation of decision process, and subjective evaluation of decision outcome (Churchill 1979). These analyses yielded results similar to that of the overall confirmatory factor model. The Cronbach alpha reliabilities of the factors are presented in Tables 2b–d and range from 0.56 to 0.96.

As objective outcomes of using the DSSs, we measured the incremental revenue obtained by the teams and the quality of the recommendations and their justifications as judged by outside experts. The items listed in Table 2a require additional description.

Table 2a Summary of Objective Decision Outcome Variables and Measures

Construct	Definition/Description	ABB	Syntex
Incremental return	Estimated incremental sales (ABB) or incremental profit (Syntex) associated with a recommended course of action.	Mean = 4,135	Mean = 260,368
Expert rater's evaluation	Single item overall judgment provided by experts (1–100 scale).	Mean = 57.6	Mean = 48.9

Table 2b Summary of Subjective Evaluation of Decision Outcome Variables and Measures

Construct	Description	ABB	Syntex
Decision satisfaction	The self-reported subject's summary affective response to the decision that the team reached. We developed the scale. *Five-item Likert scale* (*normalized* 1–5) I am satisfied with it. It is of high quality. I am in full agreement with it. I like it. I am confident that it will work out well.	Mean = 4.00 Alpha = 0.90	Mean = 3.14 Alpha = 0.94

Table 2c Summary of Group Decision Process Variables and Measures

Construct	Description	ABB	Syntex
Effort	The self-reported extent of mental effort deployed by the subject in making the decisions (note that almost all effort in this task is mental; there is little physical effort involved). Scale developed by us. *Three-item Likert scale* (*normalized to* 1–5) We were totally immersed in resolving this problem. We took this task seriously. We put in a lot of effort.	Mean = 4.36 Alpha = 0.73	Mean = 4.11 Alpha = 0.79
Discussion quality	The self-reported extent to which discussions by subjects were relevant for resolving the problems. Scale was adapted from Miranda and Saunders (1995). *Three-item Likert scale* (*normalized to* 1–5) Our discussions were well organized. We had discussions about what criteria to use to select amongst the various decision alternatives. We both participated actively in our deliberations.	Mean = 4.32 Alpha = 0.58	Mean = 3.95 Alpha = 0.59
Decision alternatives considered	The self-reported extent to which the decision process involved detailed consideration of various decision alternatives. Scale was adapted from Miranda and Saunders (1995). *Two-item Likert scale* (*normalized to* 1–5) We had discussions about many decision alternatives that were not part of the final recommendation. We considered several alternatives carefully.	Mean = 3.54 Alpha = 0.56	Mean = 3.66 Alpha = 0.65

Table 2d Summary of Subjective Evaluation of the Group Process Variables and Measures

Construct	Description	ABB	Syntex
Process complexity	The self-reported complexity of the decision-making process faced by the team in resolving the decision problem. We developed the scale. *Three-item Likert scale* (*normalized to* 1–5) It was a complex process. It was a challenging process. It was a difficult process.	Mean = 3.57 Alpha = 0.87	Mean = 4.05 Alpha = 0.91
Learning	*This is the self-reported change in the subject's skill and knowledge* as a result of completing the problem-solving exercise. Scale adapted from Alavi (1994). *Three-item Likert scale* (*normalized to* 1–5) It increased my skills in critical thinking. It increased my ability to integrate facts. It showed me how to focus on identifying the central issues.	Mean = 3.59 Alpha = 0.82	Mean = 3.27 Alpha = 0.86
Perceived usefulness	The self-reported degree to which the subject believes that using a DSS would enhance his or her performance. Scale adapted from Davis (1989). *Three-item Likert scale* (*normalized* 1–5) It enabled us to make decisions more quickly. It increased our productivity. It improved our performance.	Mean = 4.15 Alpha = 0.91	Mean = 3.44 Alpha = 0.96

Incremental Return Computation. For both cases, there is information in the research papers cited earlier about the resource allocation plans actually adopted by the firms and the incremental return (profits in the Syntex case and incremental sales revenue for ABB) that can be attributed to these plans. That information allows us to calibrate a scoring rule to determine what the incremental return would be for *any* recommendation made by a team.

While the Syntex model is an "optimization model," it also permits the user to specify different constraints on the total amount to spend and the upper and lower bounds on per-product spending, to change projected product profit margins, to run sensitivity analyses on different response functions, and the like. Hence, no single "optimization" is right, and the subjects are urged to run scenarios and consider organizational and resource constraints in making their recommendations. The ABB model is not an optimization model; rather it provides information about the likely response of individually targeted customers and prospects. The test condition, in which the DSS provides purchase probabilities, allows knowledgeable users to develop better targeting plans rule than in the control condition, where those probabilities are not provided. It is important to note that in this research, as in management practice, there is no single optimal solution; hence, we frame our assessment procedure both in terms of incremental return calculation (for objective results) and expert judgments (for subjective assessments).

ABB Incremental Return Calculation. For ABB, we used the market results reported in Gensch et al. (1990, Table 3, p. 16).

- There is no impact on incremental revenue from additional effort deployed on customers who are loyal to ABB or loyal to competitors. Specifically, if either ABB or a competitor had a purchase likelihood statistically significantly higher than that of its closest competitor, ABB saw no gain in targeting these customers.
- There is a 30% gain from customers who had a slightly lower probability of purchasing from ABB (but not significantly so) than from their most preferred supplier. ABB would then see a 30% gain, on average, from targeting these customers (called *switchables*).
- There is a 31% gain from customers who had a slightly higher probability of purchasing from ABB (but not significantly so) than from their next most preferred supplier. ABB would then see a 31% gain, on average, from targeting these customers (called *competitives*).

We used the choice probabilities computed by the model to identify the largest 20 of the vulnerable customers (switchables and competitives). We then computed the expected incremental sales from each targeted customer as: zero if not a switchable or competitive customer, and otherwise equal to adjustment factor $*$ ((1 − P(buying from ABB)) $*$ max sales potential). This formula determines the incremental return that ABB gets either by retaining a customer who would otherwise likely have switched to a competitor, or by gaining a new customer who currently marginally prefers one of the competitors. We computed the adjustment factor (=0.40) to obtain the overall sales increase from switchables and competitives of 30.5% to be consistent with the actual results that ABB realized. DSS users had the information in Figure 2 to work with; they had to develop their own financial targeting rule, albeit with better information than the Excel-only users.

Syntex Incremental Return Calculation. Syntex's actual market performance (three years forward) closely matched what the managerially generated judgmental response functions had predicted. Hence, we used the following estimate of profit per product:

$$\begin{aligned}&\text{Profit for Product } i\\&\quad=\left[\text{base sales}_i\times\text{Response}_i\left(\frac{X_i}{\mathit{base}\ X_i}\right)\times\text{margin } i\right]\\&\qquad-[X_i\times\text{salesman unit cost}],\quad\text{where}\end{aligned}$$

X_i is the sales force effort level deployed on product i, and $\text{Response}_i(X_i/\mathit{base}\ X_i)$ is the judgmentally calibrated response function assessed at X_i.

We summed these profit figures over all products to yield an overall company profit for a team's recommendation. As an example for Naprosyn, if the recommendation is for 145 reps (approximately $1.5\times$ 96.8 reps), then, from Row 9 of Figure 3, we get

$$\begin{aligned}&\text{Naprosyn profit}\\&\quad=\$214{,}400{,}000\times1.26\times0.70-\$63{,}000\times145\\&\quad=\$179{,}965{,}000.\end{aligned}$$

Note that the DSS automates the estimation of the response function and invokes Excel's Solver optimization module to help with such calculations (i.e., the estimation of the 1.26 response factor above resulting from the 50% increase in the sales force allocation to Naprosyn). As noted earlier, the DSS also permits the user to impose upper or lower limits on overall sales force spending or on spending on individual products. Excel-only users had all the input data needed to build the response function (i.e., data in cells G9–J15 in Figure 3), but not the response functions themselves.

Table 3 Overall, Main Experimental Results on DSS vs. No DSS Conditions

	ABB			Syntex		
DSS impact measure	No DSS mean (std. dev.)	DSS mean (std. dev.)	Total mean (std. dev.)	No DSS mean (std. dev.)	DSS mean (std. dev.)	Total mean (std. dev.)
Objective decision outcomes						
Incremental revenue	3,219 (1,945)	5,052 (1,821)	4,135 (2,084)	252,918 (16,477)	267,553 (13,535)	260,368 (16,638)
Expert evaluation	56.43 (13.53)	58.75 (12.87)	57.59 (13.13)	47.86 (18.31)	50.00 (16.91)	48.93 (17.51)
Subjective evaluation of decision outcomes						
Decision satisfaction	3.79 (0.87)	4.20 (0.64)	4.00 (0.78)	2.78 (1.13)	3.47 (0.92)	3.14 (1.07)
Decision process						
Effort	4.49 (0.53)	4.23 (0.62)	4.36 (0.59)	3.92 (0.78)	4.30 (0.58)	4.11 (0.71)
Discussion quality	4.30 (0.65)	4.34 (0.37)	4.32 (0.52)	3.75 (0.68)	4.14 (0.45)	3.95 (0.60)
Decision alternatives considered	3.64 (0.97)	3.43 (0.77)	3.54 (0.87)	3.57 (0.98)	3.75 (0.74)	3.66 (0.86)
Subjective evaluation of the decision process						
Complexity	3.77 (0.77)	3.36 (0.70)	3.57 (0.76)	4.21 (0.82)	3.89 (0.80)	4.05 (0.82)
Learning	3.77 (0.84)	3.41 (0.79)	3.59 (0.83)	3.29 (1.01)	3.26 (0.99)	3.27 (0.99)
Perceived usefulness of DSS	4.11 (0.89)	4.19 (0.94)	4.15 (0.91)	3.05 (1.40)	3.82 (1.20)	3.44 (1.35)

Expert Rater's Evaluations. All groups completed a recommendation form for each case, along with their justifications for these recommendations. We transcribed and typed these recommendation forms to make them appear uniform, and gave them to three expert raters for evaluation. We removed references to the form of the DSS that the respondents had available so that the raters would not know whether the groups had had access to a DSS to aid their decisions. The raters were senior faculty members in marketing and management science at two leading universities and were knowledgeable about the specific problem context and resource allocation issues in general. We provided the raters with the cases and the accompanying software, but provided no indication of "right" answers. We then asked the raters to score the overall quality of the recommendations on a scale of 1–100.

Results

To test the significance of the effects of our experimental manipulations, we conducted a series of analysis of variances (ANOVAs) with repeated measurements. Within each team, we treated measures for the two subjects as the repeated measures for the same dependent variables. As independent variables, we included DSS availability and order. Further, we included the interaction between DSS availability and order to analyze whether the effect of a model would be different if a case were analyzed first or second. The structure of the ANOVA model is as follows:

$$\begin{aligned}&\text{DSS impact variable}\\&\quad=\beta_0+\beta_1*\text{DSS availability}+\beta_2*\text{order}\\&\qquad+\beta_3*\text{DSS availability}*\text{order}.\end{aligned}$$

The significance levels we report in this section are based on an analysis of the complete model that includes the two main effects and their interactions.

DSS Impact on Objective Decision Outcomes

We start by testing Hypothesis 1; namely, that the use of a DSS improves objective decision outcomes.

Incremental Return. The results in Table 3 show that for both ABB ($F=12.82$, p[3] <0.001) and Syntex ($F=12.63$, $p<0.001$), DSS-aided groups achieved higher incremental returns than did Excel-only aided groups. No significant order effects appeared. These results support Hypothesis 1a.

Expert Evaluation. In neither of the two cases did the experts rate the recommendations of the DSS-aided teams higher than those of the Excel-only aided teams (ABB: $F=0.43$, $p=0.257$; Syntex: $F=0.20$, $p=0.329$). Thus, we did not find support

[3] All significance levels in the "Results" section represent one-tailed tests.

for Hypothesis 1b. To understand why, we ran exploratory regression analyses, regressing expert ratings against different explanatory variables. We found that report length—the number of words in the written explanations provided by the subjects for their recommendations—was, by far, the most significant factor explaining expert ratings for both ABB and Syntex (ABB: $\hat{\beta}=0.52$, Syntex: $\hat{\beta}=0.73$). That is, the more detailed the explanation for a recommendation, the better the raters evaluated that recommendation, regardless of the experimental condition to which a team belonged. For Syntex, there is a marginally significant (positive) effect of deanchoring, but that effect is much less important than the report-length effect.

We hypothesize that in the absence of objective performance indicators, expert raters employ potentially biasing cues, such as the length of the report, in making an assessment of the quality of the recommendations. To test for this possibility, we estimated a regression model of expert ratings as a function of (1) the DSS availability and (2) performance cues—i.e., report length and the extent of deanchoring—that may or may not be associated with actual decision quality. Table 4a summarizes our results. Given the high level of significance of report length as a cue in both cases, we also explored the potential determinants of report length, summarized in Table 4b. Our analyses suggest that there is an underlying trait, namely, the tendency to write long reports, that is not only distinct from team performance (Table 4b), but is also the main driver for report length (ABB: $\hat{\beta}=0.52$, Syntex: $\hat{\beta}=0.52$). Thus, report length seems to be a primary cue that leads to judgmental bias on the part of the expert raters.

Summarizing, we find (not surprisingly) that high-quality, model-based DSSs significantly improve the quality of decision making, i.e., teams using the DSS significantly improve their firm's profitability. However, somewhat surprisingly, the use of the DSS does not significantly affect the way their recommendations are perceived by the (surrogate) senior managers, represented by the expert judges.

Table 4a **Determinants of Expert Ratings (Standardized Regression Coefficient, *t*-Value in Parentheses)**

Variable	Syntex Case	ABB Case
DSS availability	0.11 (1.05)	−0.00 (−0.03)
Cue: Report length[1]	**0.73 (7.85)**	**0.52 (4.40)**
Cue: Deanchoring[1]	**0.22 (2.20)**	0.15 (1.16)
F	$F(3,51)=23.44$ $p=0.00$	$F(3,52)=7.22$ $p=0.00$
R-square	0.58	0.29

Table 4b **Determinants of Report Length (Standardized Regression Coefficient, *t*-Value in Parentheses)**

Variable	Syntex Case		ABB Case	
DSS availability	−**0.36** (−**2.84**)	−0.30 (−2.00)	0.05 (0.35)	0.07 (0.45)
Incremental return	**0.27 (2.12)**	0.22 (1.49)	−0.16 (−1.15)	−0.01 (−0.03)
"Group's tendency to write lengthy reports"[2]	**0.52 (4.57)**		**0.52 (4.01)**	
F	$F(3,51)=9.01$ $p=0.00$	$F(2,52)=2.23$ $p=0.12$	$F(3,52)=5.47$ $p=0.00$	$F(2,53)=0.14$ $p=0.87$
R-square	0.35	0.08	0.24	0.01

Note. Differences significant at the 0.05 level (one tailed) are shown in bold.

[1]The factor report length is the number of words used in the team's recommendation for Syntex and ABB, respectively. Deanchoring, i.e., deviation of decision from anchor point, is calculated as follows: (1) ABB: 20—number of targeted firms that belong to the set of the 20 firms with the highest purchase volume and (2) Syntex: Euclidean distance from the base allocation. The variables deanchoring (Syntex only) and report length (both cases) were log transformed.

[2]To approximate the team trait of writing extensively, independent of any performance measures, we used the report length (log transformed) of ABB in the case of Syntex and vice versa.

DSS Impact on Subjective Evaluations of Decision Outcomes

Next, we test Hypothesis 2, which states that the DSS has no effect on the decision makers' subjective evaluations of their decisions.

Decision Satisfaction. For ABB, the effect of the DSS on decision satisfaction is highly dependent on whether this case was analyzed first or second (after the Syntex case) ($F = 15.82$, $p < 0.001$). On average, DSS availability does not increase decision satisfaction ($F = 1.16$, $p = 0.144$). However, overall (including those with and without DSS), subjects were more satisfied with their recommendation if they analyzed the ABB case after they had first analyzed the Syntex case (4.12 versus 3.87, $F = 4.33$, $p = 0.022$). If the ABB case is analyzed first, the DSS was effective in increasing decision satisfaction (4.17 versus 3.44 for the DSS group versus the Excel-only aided group, $F = 8.826$, $p = 0.003$). The satisfaction enhancing effect did not show up if the ABB case was analyzed after the Syntex case. For Syntex, we do find a significant main effect of DSS availability ($F = 4.095$, $p = 0.024$). DSS-aided subjects report more satisfaction with their recommendations than do Excel-only aided subjects (3.47 versus 2.78). This DSS effect holds irrespective of the order in which the cases are analyzed. Overall, subjects are more satisfied with their recommendations for ABB than for Syntex (4.00 versus 3.14). Summarizing, for the Syntex case, DSS use increases decision satisfaction, which leads us to reject Hypothesis 2a, whereas we find partial support for Hypothesis 2a for the ABB DSS.

DSS Impact on Decision Process

Next, we test Hypothesis 3, which states that the DSSs will have mixed effects on the decision process.

Effort. For the ABB case, we find that DSS availability does not have a significant main effect on perceived effort. In fact, there is a tendency for the DSS to reduce the amount of effort (4.49 versus 4.23; $F = 2.02$, $p = 0.081$). However, similar to the effect for decision satisfaction, the ABB-DSS effect depends on whether the case is analyzed first or second ($F = 3.78$, $p = 0.029$). If the ABB case is analyzed first, the DSS only marginally affects the amount of effort expended. If the ABB case is analyzed after the Syntex case, the DSS leads to a substantial reduction in effort (4.17 versus 4.57), which supports Hypothesis 3a. For Syntex, while we find that DSS use increases the amount of effort deployed in analyzing the case (3.92 versus 4.30), the effect is not significant ($F = 1.82$, $p = 0.092$). Hence, we find some support for Hypothesis 3a, but only for the ABB case.

Discussion Quality. Overall, the ABB DSS does not significantly improve the perceived quality of the discussions ($F = 0.35$, $p = 0.228$). However, as before, the effect of the ABB DSS differs depending on order ($F = 2.99$, $p = 0.045$). If the ABB case was analyzed first, DSS availability improves discussion quality (4.14 versus 4.32); if the ABB case was analyzed second, the DSS had little impact on discussion quality. For the Syntex DSS, we find that discussion quality improves with the availability of the DSS (4.14 versus 3.75; $F = 3.23$, $p = 0.039$). This effect does not depend on the order in which the cases were analyzed. In summary, with respect to discussion quality, we find support for Hypothesis 3b for the Syntex DSS and partial support for the ABB DSS.

Decision Alternatives Considered. We find no support for Hypothesis 3c for either case: DSSs did not significantly affect the number of decision alternatives generated or evaluated (ABB: $F = 0.19$, $p = 0.333$; Syntex: $F = 0.019$, $p = 0.446$). The order in which the cases were analyzed also did not influence the number of alternatives generated. It appears that DSS can influence objective outcomes even without altering some key aspects of the decision process, such as the number of alternatives evaluated during decision making. Miranda and Saunders (1995) report a similar result.

DSS Impact on Subjective Evaluations of Decision Process

Lastly, we test Hypothesis 4, which states that a DSS will have mixed effects on the evaluation of the decision process.

Complexity of the Decision Problem. Hypothesis 4a hypothesizes a net zero effect of DSS use. However, for both the ABB and the Syntex case, we find that the perceived complexity of the problem-solving task is reduced with the availability of a DSS. Overall, the Syntex case is perceived to be more complex than the ABB case (4.05 versus 3.57). Analyzing the ABB case is perceived to be significantly less complex if it is analyzed second than if it is analyzed first ($F=3.85$, $p=0.028$). Additionally, the ABB DSS reduced the perceived complexity of the decision problem ($F=5.29$, $p=0.013$). For the Syntex case, we do not find an order effect, and further, the effect of the DSS is not as strong ($F=2.76$, $p=0.052$). For Syntex, there was no difference in perceived effort between the DSS and Excel-only conditions (Hypothesis 3a), and yet we find perceived problem complexity is lower with DSS use. This suggests that the directive Syntex DSS (i.e., a DSS that offers specific feedback) has a different type of effect on the decision process than does the nondirective ABB DSS. Overall, we reject Hypothesis 4a.

Learning. The ABB DSS does not enhance learning as perceived by the participants. In fact, DSS users report a lower learning experience than do Excel-only aided users (Excel: 3.77 versus DSS aided 3.41; $F=2.24$, $p=0.141$), as hypothesized in Hypothesis 4b, and this effect is more prominent if the Syntex case is analyzed first ($F=2.24$, $p=0.071$). However, the effect is not significant. The Syntex DSS also had no impact on the amount of perceived learning ($F=0.026$, $p=0.436$). Thus, overall, we find no support for Hypothesis 4b. Presumably, to the extent that a DSS automates parts of the decision process and hides complexity, it may well lead to a reduction in perceived learning.

Perceived Usefulness of the DSS. On average, the DSS for ABB is not perceived as significantly more useful than the Excel-only aid ($F=0.17$, $p=0.341$). However, there was an interaction between DSS availability and order ($F=5.501$, $p=0.012$), such that the DSS is perceived as useful if the ABB case is analyzed first. If the Syntex case is analyzed first, the ABB DSS is not perceived as useful. For Syntex, we find a strong effect of DSS availability ($F=6.618$, $p=0.007$): The DSS is perceived as useful (3.82 versus 3.05). This result does not depend on the order in which the cases were analyzed. Hence, we find support for Hypothesis 4c for the Syntex model and partial support for Hypothesis 4c for the ABB model. Again, this result shows the importance of deploying a more directive DSS, such as Syntex, to influence perceived usefulness of a DSS.

In summary, our results show that both the ABB and the Syntex DSS improve objective performance by leading to higher incremental returns. The effects of the DSSs on objective performance variables are more pronounced than their effects on subjective variables, especially for the ABB DSS. The ABB DSS only improves decision satisfaction if it is analyzed first, before the subjects had gained any experience in addressing a resource allocation problem. In such situations, subjects also perceived the ABB DSS as more useful, and as improving discussion quality. When the ABB case is analyzed second (i.e., after the Syntex case), the DSS was not perceived as more useful than the Excel-only tool, DSS use reduced perceived effort, there was no improvement in perceived discussion quality, and the subjects reported less satisfaction with their decisions. The Syntex DSS was perceived as useful regardless of whether the Syntex case was analyzed first or second. The Syntex DSS improved discussion quality, improved decision satisfaction, and appeared to have increased effort as well.

Discussion and Conclusion

Our results show that two well-designed decision models for marketing resource allocation improve objective outcomes, primarily because those DSSs enabled subjects using them to move away from historic anchors (the base-case decision scenarios), toward decisions that improve organizational profits. Specifically, for ABB, DSS users targeted more "switchable and competitive" customers (average 12.8 customers out of the best 20 to be targeted) than did Excel-only users (average 6.3 customers), compared to the anchor (targeting large customers), which included 6 switchables and competitives. For Syntex, DSS users recommended 270 incremental salespeople on average, versus 175 by Excel-only users and 120 under the current management plan (the anchor). The Syntex DSS users also recommended more effort deployment on the profitable product, Naprosyn, than did either the Excel-only group or the current management plan (38% of total sales resource effort in the DSS group versus 30% for the Excel-only group and 23% under the current management plan). Hence, a DSS appears to provide users with the confidence and the support to propose decisions farther away from the status quo than those without a DSS.

DSS effects on subjective perceptions of achieved outcomes, however, were mixed and somewhat surprising. For Syntex, DSS use enhanced perceived satisfaction with the outcome and the perceived usefulness of the DSS. In contrast, for ABB, the DSS did not always increase satisfaction with the outcome and the perceived usefulness of the model. Even though the use of DSSs reduced subjects' perception of problem complexity, they had no significant positive impact on perceived learning and may even have reduced it. By investigating DSS effects on the decision process separate from its direct effects on objective performance, we find a surprising disconnect between objective performance measures that are favorable and subjective performance measures (e.g., satisfaction and usefulness) that are mixed or unfavorable.

As discussed earlier, DSSs can alter the trade-offs that decision makers make between effort deployment and quality of decisions. A DSS could just improve efficiency (save effort). Or it could also lead to greater effectiveness *if* the user is motivated by the DSS to deploy more cognitive effort to the task (Moore and Chang 1983). Our results indicate that both the Syntex DSS and the ABB DSS reduced the perceived complexity of the problem. For the directive Syntex DSS, there was no reduction in effort even though perceived complexity did decrease; whereas for the nondirective ABB DSS, we did not find similar effects, especially if the ABB DSS was used after the subjects analyzed the Syntex case. These results suggest that the design of a DSS (e.g., directive versus nondirective) influences whether decision makers choose effort reduction over decision-quality improvement.

The mixed results with respect to subjective and objective outcomes also offer insights about why we do not see widespread use of DSS in tasks such as resource allocation. It is not enough to simply promise, or even deliver, improved objective outcomes through DSS use. It is equally important to design DSSs so they give users cues to help them perceive that improved outcomes are likely to occur with their use (as was the case with the Syntex DSS). And expert evaluations of decisions seem to be driven as much by style as by substance. Hence, if DSSs generate a cost for the organization without a clearly perceived benefit (improved perceived decision quality), they are unlikely to be widely used, even when their use is likely to be beneficial.

The effect of the order variable highlights the potential differences between directive and nondirective DSS (Syntex versus ABB). Our postexperimental questionnaire supports our observation that feedback from the Syntex DSS influenced the decision process in a different way than in the ABB case. In the Syntex case, the means for the item "The DSS narrowed our focus" were statistically significantly different between DSS and Excel-only groups, whereas they were not different for the ABB case groups. In the framework of Balzer et al. (1989), user interactions with the Syntex DSS (but not with the ABB DSS) provided "cognitive feedback," linking the task with the environmental performance measures.

Our study also shows that DSSs can help reduce the perceived cognitive complexity of a resource allocation task, suggesting that their use is more likely when the problem, such as resource allocation, is intrinsically complex. While we believe our results will generalize beyond the resource allocation context, we also note that resource allocation is an important and significant context in itself. For example, Sinha and Zoltners (2001) recount more than 2,000 applications similar to that of Syntex in their consulting practice alone.

While our results suggest the need for further research, especially concerning the role of discussion facilitation and feedback, they also offer the following insights for DSS design.

(1) *Design DSSs to encourage discussion*. Although designing DSSs that lead to improved objective outcomes should be a primary criterion, that criterion alone is not enough to encourage use of the DSS, or to help users feel good about DSS use; what decision makers perceive (i.e., subjective assessment) is not what they actually achieve (objective outcomes). To make subjective outcomes more commensurate with objective outcomes, it is important to design in features that encourage interaction with the DSS, offer explanations for recommendations, generate visual outputs, and provide structured cognitive and outcome feedback, all of which can facilitate managerial discussion quality about the decision problem and enhance perceived outcomes from DSS use (satisfaction, learning, and usefulness of the DSS).

(2) *Design DSSs to reduce problem complexity and encourage consideration of additional alternatives*. When

a DSS reduces problem complexity and facilitates the assessment of multiple alternatives, decision quality improves (as was the case with Syntex DSS). This improvement appears to occur because such DSSs induce users to deploy more cognitive effort toward problem solving.

(3) *Design in feedback*. Users experience improved decision processes and better outcomes when the DSS fits well with the decision context, and provides specific feedback on the likely outcomes of alternative courses of action. Users are likely to prefer DSSs that they understand and trust—to increase perceived usefulness of the DSS, it is important to make the operation and the logic of the DSS more transparent (as with the Syntex DSS versus the ABB DSS).

The above suggestions for DSS design are, naturally, incomplete. Other factors, such as ease of use, compatibility with existing systems, alignment of personal and organizational reward metrics, and the like that have been identified in the adoption literature (e.g., Rogers 2003) are also required to increase the intent to adopt.

We conclude by noting some limitations of this research that suggest opportunities for future research questions. Our study is based on a laboratory experiment, with limited duration, and without all the political complexities associated with DSS use in organizational settings. We did not manipulate or explore several contextual aspects of DSS use that are likely to influence the process and outcomes associated with DSS. For example, we fixed the (same) maximum experimental duration time for all subjects, preventing us from fully understanding the drivers of (objective) effort expenditure in a more unconstrained environment. In addition, in practice, people are trained specifically in the use of a DSS, which we did not do here to avoid inducing another strong anchor point for the decisions to follow. And, it may be that managers in real situations are better able to distinguish good recommendations from poorer ones, in contrast with our laboratory situation. These issues suggest the need for field research (preferably using experimental techniques) in the context of the introduction of a DSS in real organizations. And while we attempted to study learning and likely adoption in a single laboratory setting, it may be much more realistic and appropriate to study learning, feedback, and their effects in a repetitive decision environment.

In recent years, companies have invested tens of billions of dollars in implementing software systems, such as customer relationship management, to facilitate marketing resource allocation decisions. Without a careful understanding of how such systems influence individual and organizational decision making and performance, it is likely that these investments will not be optimally leveraged. This situation presents many rich research opportunities for developing generalizations about what types of DSS will work well in such software environments and why. We hope that the work presented here can play a part in helping to affect both the theory and practice of DSS implementation.

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