HOW AND WHY DECISION MODELS INFLUENCE MARKETING RESOURCE ALLOCATIONS

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Abstract

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We test hypotheses about the effects of DSSs in a controlled experiment with two award winning DSSs and find that, (1) DSSs improve users’ objective decision outcomes (an index of likely realized revenue or profit); (2) DSS users often do not report enhanced subjective perceptions of outcomes; (3) DSSs, that provide feedback in the form of specific recommendations and their associated projected benefits had a stronger effect both on the decision making process and on the outcomes.

Our results suggest that although managers actually achieve improved outcomes from DSS use, they may not perceive that the DSS has improved the outcomes. Therefore, there may be limited interest in managerial uses of DSSs, unless they are designed to: (1) encourage discussion (e.g., by providing explanations and support for the recommendations), (2) provide feedback to users on likely marketplace results, and (3) help reduce the perceived complexity of the problem so that managers will consider more alternatives and invest more cognitive effort in searching for improved outcomes.

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Key Words: DSS, Marketing Models, Decision Quality, Decision Process, Resource Allocation

1. Introduction

A common managerial decision problem is the budgeting and allocation of resources: for example, how large should the budget be (e.g., for advertising, for sales promotion, for sales-force effort, etc.), and how should that budget be allocated over geographies, products, market segments, and over time. Most management scientists share the belief that model-based decision support systems (DSSs) can help improve such decisions. However, there is little evidence either to support or to contradict this belief. In this paper, we formulate and test a conceptual framework to understand the effects of DSSs on budgeting and resource allocation decisions (which we shorten to "resource allocation decisions" for conciseness). Our framework articulates *how* DSSs influence the decision process (e.g., cognitive effort deployed, discussion quality, and number of decision alternatives generated), and as a result, *how* these DSS's influence decision outcomes (e.g., profit, satisfaction, and learning). We focus on marketing resource allocation, specifically on sales effort allocation, and customer targeting.

Since the late 1970's researchers have studied the effects of DSSs on managerial decision making. Table 1 summarizes a number of these studies, both within and outside the marketing field, including those that specifically address resource allocation decisions. Most studies have focused primarily on exploring *whether* the use of DSSs 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), and 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 those that have studied the decision process have not clearly explored how the DSS jointly influences the process and the outcomes.

Past studies also report mixed results regarding DSS effects on outcomes: while most report that DSSs improve resource allocation decisions in marketing, Chakravarti, Mitchell, and Staelin (1979) report that the use of a DSS had a detrimental effect on decision quality. The broader DSS research also reports mixed findings in laboratory studies about the effects of DSSs on decision outcomes (See Sharda, Barr, and McDonnel 1988 or Benbasat and Nault 1990). Of the eleven studies Sharda et al.

reviewed, six showed improved performance due to DSS use, four showed no difference, and in one study, performance actually decreased for DSS users. It remains unclear what decision processes caused the reported effects of the systems. Only a few studies have explored *why* DSS influence the process of decision making (e.g., Hoch and Schkade 1996; Van Bruggen et al. 1998), but these studies have not explored the full spectrum of effects of the DSS on the process, particularly in the context of a resource allocation task. Another concern with the prior studies is that the field studies lacked experimental control (e.g., Fudge and Lodish 1977) although they used DSS to address actual managerial problems. On the other hand, although lab studies imposed experimental controls, they addressed "made up" problems. One unique aspect of our study is that we use a lab study using a real world case for which externally validated actual results are known (i.e., decision quality is not determined endogenously).

Insert Table 1 about here

Thus, a review of the literature leaves a number of questions unanswered:

1. What does it mean for a DSS to be "good?" Specifically, is there a relationship between the decision problem, the type of DSS, the decision making process, and the outcome or quality of the actual decision (which may differ from the output of the DSS).
2. What are the relationships between decision context (e.g., anchor or reference condition), the DSS-supported decision process, and decision quality?
3. Is the effect of the DSS on the decision process and the decision outcome robust, or is it specific to the context or DSS design criteria?

Our research addresses these issues as follows:

1. *Comprehensive Assessment of DSS Impact*. We incorporate objective measures *and* subjective perceptions of both the decision process and the decision outcomes, including multiple dependent (outcome) *and* mediating (process) variables. Most of the earlier studies have only focused on outcome variables (e.g., profit, satisfaction, and decision confidence), and have ignored how decision

processes influence outcomes. In our research, we not only evaluate whether a DSS influences outcomes, but also *why* and *how* that influence comes about through changes in the decision process.

2. *Anchor and Adjustment Process*. Resource allocation decisions get made in managerial contexts characterized by historical precedents ('What was last year's plan?"), or by relying on existing common benchmarks or reference points (e.g., based on rules of thumb, such as "match the industry Advertising-to-Sales ratio" (Rossiter and Percy, 1997)). To study how DSS influence managers' reliance on anchor points, we explicitly assess whether DSS use leads to departure from anchor points.

3. *Study Context*. Unlike most previous studies, we do not simply compare a DSS versus no-DSS treatment, an unrealistic comparison. Instead, we manipulate the nature of the decision support provided to the users, where all users have access to the same background information, the same incentives to perform well and the same computer and analytic platform (Excel in our case). Thus, subjects in the non-DSS condition, as with those in natural settings, have access to and can manipulate the same data as the DSS subjects. That is, we study the differences in process and performance between contexts where one set of users have access just to a DSS tool (Excel), whereas other users have access to a specific model-based DSS. In the rest of the paper, when we say DSS, we explicitly mean the model-based DSS. When we refer to non-DSS, we mean that subjects have access only to the data and the Excel tool. We employ a mixed within/between-subjects experimental design, in which each subject is exposed to two different DSS-decision situation combinations, permitting us to also evaluate learning effects, if any.

4. *DSS-Problem Relationship*. Much experimental work in DSS effectiveness has dealt with situations where, ex post, there is a right answer, such as in a forecasting task. In resource allocation situations, there are no objective right answers at the time a decision is being made, and decision makers can rarely observe the impact of their decisions on firm performance *relative to the impact of other decision alternatives*. For such situations, we hypothesize that DSSs will deliver the same general patterns of decision process and outcome improvements across problem contexts. (As we will see later, our results do not support this hypothesis, thereby offering interesting further research questions.)

Overall, our results show that subjects who used the DSS made decisions farther away from the anchors and achieved better outcomes than those without a DSS. However, access to a DSS did not result in a clear pattern of direct impact on subjective measures of performance like "satisfaction," learning" and "usefulness." Furthermore, expert judges (acting as surrogates for managers) often could not distinguish good decisions from poorer ones. While the DSSs *did* have significant effects on the decision making process, the different DSS-environments that we studied showed different patterns of effects.

The paper is organized as follows. In the next section, we describe our conceptual framework and develop specific hypotheses. Then we describe our experimental setup and the methodology for testing our hypotheses. The subsequent section provides the results of our analyses. We conclude by discussing the implications of our study for DSS design, and identify future research opportunities.

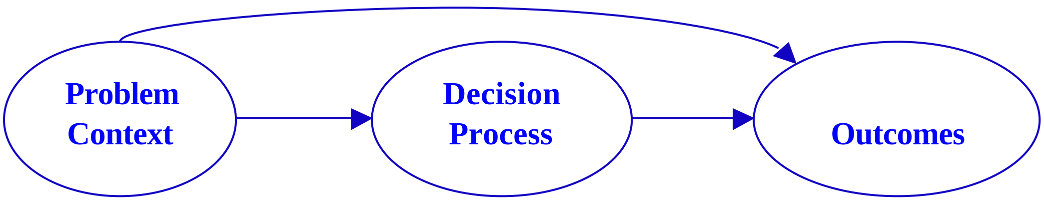
2. Hypotheses Development

Although there is a substantial amount of research that has tested whether a DSS improves outcomes, it is surprising how little we know about ***how*** a DSS influences decision processes (Wierenga and Van Bruggen, 2000). It is possible for a DSS to influence the decision process without affecting the decisions made, or the outcomes that result from those decisions. For example, decision makers may choose to go with their prior beliefs (i.e., no change in outcome), after considering some additional options prompted through interactions with the DSS (i.e., change in process). It is also possible for a DSS to influence decision outcomes without significantly influencing the decision process, which could occur if, after going through their normal decision processes, the decision maker decides that "the DSS knows best" and simply adopts its recommendations. And a DSS could change the decision process and, through these changes, influence decision outcomes. Unless we separate the effects of a DSS on the decision process from its effects on outcomes, we will be unable to articulate *why* and *how* a DSS leads to different decision outcomes.

Generally, decisions emerge through an interaction of a user with a DSS, and through the active mental processing that takes place (Vandenbosch and Higgins 1995). As a result, DSSs often have multi-faceted effects on both decision processes and on the outcomes of these processes. DSSs can help decision makers develop a better understanding of the decision problem, through improved formulation of the problem using the system, generating new decision alternatives, improved evaluation of potential courses of action (e.g., “anticipatory learning”), or from inductive learning across multiple exposures to and use of one or more DSSs.

This improved understanding is then internalized by the decision-makers, who adjust their decision making process accordingly.

The following schematic diagram summarizes the above discussion.



Decisions result from an underlying decision process, which can be characterized by such variables as the amount of cognitive effort that people put into solving a problem, the quality of the discussions they have during the decision process, the number of decision alternatives they generate, and so on. Both the decision outcomes and the decision process, in turn, will be influenced by the context in which the decision maker is operating. This context can be described by the characteristics of the decision environment, the characteristics of the decision makers who must resolve the problem and the characteristics of the available decision aid.

The Effects of DSSs on Decision Processes and Decision Outcomes

Several researchers have argued, and empirically demonstrated, that a combination of DSS and human decision makers will outperform unaided decision makers (Blattberg and Hoch 1990; Hoch 1994; and Hoch and Schkade 1996). The main reason for this finding is that models have strengths that can compensate for the weaknesses of human decision makers’ decision making processes, i.e., DSSs cause changes in the processes by which decisions are made (Silver 1990).

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 relatively short time frames, these limitations encourage people to use heuristic approaches to resolve the problem. Although heuristics can reduce cognitive effort, they can also lead to systematic (and predictable) errors. An example heuristic is *anchoring and adjustment*. In making decisions (e.g., determining the total advertising budget), decision makers who apply this heuristic start from an initial "anchor" point and adjust it to arrive at the final decision. The anchors may be suggested by historical precedent (e.g., the previous year's advertising budget) but could also arise from random information. However, adjustments from the anchor point often tend to be non-optimal (Slovic and Lichtenstein 1971; Mowen and Gaeth 1992). For example, in marketing resource allocation tasks, there is a tendency to allocate effort to conform to past allocations, or toward products or market segments that have strong managerial advocates instead of what might be most cost effective for the organization.

In resource allocation tasks, DSSs can help managers cope with large amounts of information, thereby reducing the need for using heuristics. Models integrate information in a consistent way (Dawes 1979). Thus, models may 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. In a resource allocation context, it is likely that these heuristics will reduce the weights assigned to objective criteria, such as the potential responsiveness of sales to increased marketing effort. 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. In view of these advantages and limitations of DSSs, we expect that a combination of human decision maker and a DSS will be more effective than a human decision maker without a DSS. We hypothesize:

H1: *The use of a DSS will improve both the subjective and objective outcomes of marketing resource allocation decisions.* And:

H2: *The use of a DSS will improve the overall process of decision making in a marketing resource allocation context.*

Effects of DSS-Induced Decision Processes on Outcomes

The extent to which a DSS improves the quality of decision-making processes and decision outcomes will depend on what the DSS has been designed to do (Silver 1990) and on how well it performs (Van Bruggen, Smidts, and Wierenga 1996). Users often adopt a "cost-benefit" approach, by which they assess the tradeoffs between decision quality and the effort they need to invest in the decision making process (Payne 1982). The actual decision will result from a compromise between their desire to make a good decision and their desire to minimize effort. Decision makers tend to favor effort reduction (Payne 1982; Payne, Bettman, and Johnson 1988) and only focus on enhancing decision quality if they expect that incremental effort will lead to a large gain (Todd and Benbasat 1992).

If a DSS is part of the decision context, it can alter this quality-effort tradeoff. However, the mere availability of DSS will not improve decision quality. A DSS could reduce cognitive effort (simplify the decision process with little or no improvement in outcome) or enrich the decision process, perhaps even leading to more effort and better results. Thus, reducing cognitive effort will not necessarily improve decision quality; decision makers must deploy the "saved effort" to explore more decision alternatives or to explore decision alternatives in greater depth to realize improved outcomes. Thus, model-based DSSs might not only improve efficiency, but might 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).

Whatever the mechanism that a DSS uses to induce decision process improvement, we hypothesize the following:

H3: *Improved overall decision-making processes in a marketing resource allocation framework will lead to significantly improved subjective and objective outcomes.*

In addition, we have no strong prior theory to suggest why certain DSS-context combinations might be more effective or efficient than others. Hence, we hypothesize:

H4: *The patterns of DSS impact articulated in H1-H3 will hold across marketing resource allocation decision contexts and DSS design criteria.*

3. Methodology

DSS researchers have used a number of research approaches, including survey-based research, theoretical modeling, field studies/case analysis and experimental laboratory research (Table 1). To test our hypotheses, our choice of methodology is driven by the following six criteria:

C1: The decision context should be replicable, to permit statistical model building and hypothesis testing.

C2: The decision context should be realistic.

C3: We should be able to assess the robustness of our results across decision contexts and DSS designs.

C4: Participants should be real decision makers or have had sufficient training in the domain to understand the issues associated with resource allocation decisions.

C5: Participants should have the background and capability to understand and use spreadsheet models and market response models.

C6: Participants must not be experts (e.g., analysts) in the use of DSSs, because our hypotheses concern decision making by typical managers.

C1 drove us to do our research in a laboratory setting. C2 and C3 had us seek at least two realistic resource allocation scenarios which had DSSs associated with them. We were able to locate two such scenarios: the ABB Electric case and the Syntex Labs (A) case as described in Lilien and Rangaswamy (1998). These cases report on resource allocation problems that ABB and Syntex addressed using decision models. Both cases are based on research that received the Edelman prize from INFORMS as outstanding examples of the practice of management science. Papers describing these models (Gensch et al., 1990 and 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.

C4-C6 led 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 sufficiently large 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 (response model-based decision support), but were also sufficiently homogenous along other dimensions to make them appropriate subjects for our research.

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 our experimental unit. We randomly assigned each team to one of eight experimental conditions (see below) to analyze and develop recommendations for both cases. All groups also received identical data (described in the cases) in the form of Microsoft Excel spreadsheets and had the full functionality of Excel available to them. The groups differed in, (1) whether their spreadsheet included an embedded DSS model that allowed the subjects to analyze the data (if they choose 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.

<u>ABB case</u>: The decision problem was to allocate a supplementary marketing budget to the "top 20" customers (out of 88 customers) to be recommended by the subjects. The data summarized how these customers viewed each of the four suppliers (including ABB) on criteria such as invoice price, technical specs of the products, availability of spare parts, etc. 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) in identifying the target customers. All subjects were told the company had historically targeted its marketing programs at its largest customers, but that a company consultant (Prof. Dennis Gensch) had introduced the concept of targeting customers by "switchability." The idea was to target those customers whose likelihood of purchase indicated 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 either loyal to competitors or who were loyal to ABB already. Switchability segmentation conflicted with prior company behavior, which was to target purely based on sales potential. We introduced the prior policy as a decision anchor for this case. Figure 1 summarizes the data that were available to all subjects, and Figure 2 summarizes the results from running the multinomial logit model (available to groups that had access to the DSS).

Insert Figure 1 and Figure 2 about here

Syntex case: The Syntex case describes the situation that Syntex Labs faced in 1982, when they had 430 sales representatives in the US 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 seven 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 force, since a relatively new product, Naprosyn, was very popular in the market and appeared to be under-promoted relative to the sales of other products on a sales per rep basis. The case describes the concept of a response model and the hiring of a consultant (Leonard Lodish from Management Decision Systems) 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 (see Figure 3). The DSS-supported group also had access to an optimization model. That model allowed subjects to determine the "optimal" sales force size and effort allocation, either on an unconstrained basis ("What is the best level of effort overall and on a product-by-product basis?") or under user-specified constraints. Those constraints could be placed either on the total size of the sales force (e.g., "What is the best allocation of effort under the current policy of adding 40 reps per year?") or on individual products ("Allocate no more than 200 reps to Naprosyn."). Figure 4 gives the results from the unconstrained effort allocation model.

Insert Figure 3 and Figure 4 about here

The ABB DSS and the Syntex DSS differ in design as well as in problem context. The ABB model does not make specific recommendations about which customers to target under various user-selected criteria; the user had to develop those criterion, nor does it provide any expected outcomes in terms of incremental sales or profits, customer acquisition, retention or the like. In contrast, the Syntex DSS makes specific recommendations for the sizes of the sales force and effort allocation, and also provides the expected profit (computed from sales response functions).. In that sense the Syntex model provides users with concrete feedback on the expected outcomes of alternative resource allocations.

The following table summarizes our eight experimental conditions. To avoid order effects, we gave half of the groups the ABB case first and then the Syntex case; the other groups did the cases in the reverse order.

Group	**First case (DSS – Yes or No)**	**Second case (DSS – Yes or No)**
1-[Control]	ABB (No)	Syntex (No)
2-[Control]	Syntex (No)	ABB (No)
3	ABB (No)	Syntex (Yes)
4	Syntex (Yes)	ABB (No)
5	ABB (Yes)	Syntex (No)
6	Syntex (No)	ABB (Yes)
7	ABB (yes)	Syntex (Yes)
8	Syntex (Yes)	ABB (Yes)

Experimental Procedure

Our experimental procedure consisted of five steps.

Step 1 Background and qualifications. After entering the lab, each subject filled out a pre-experimental questionnaire with questions about demographics (age, gender, etc.), work background, and computer and Excel experience.

Step 2: Case 1. Subjects as a group received their first case and a tutorial illustrating how the related software worked. The tutorials given to subjects with DSS contained additional information about running the DSS. All groups filled out forms summarizing their recommendations and their justification.

Step 3: Post Analysis Questionnaire 1. After completing their recommendation form, all subjects (individually) completed a post-analysis questionnaire that asked for their subjective evaluations of their case analysis, the associated discussions, their recommendations, and their assessment of the software.

Step 4 Case 2. Same as Step 2, but for the second case.

Step 5: Post Analysis Questionnaire 2. Same as Step 3, but for the second case.

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

112 first year MBA students participated in the study, making 56 groups, with 7 groups per experimental condition. We paid each subject $25 to participate in the study, which lasted about 3 hours (subjects were informed that each case would take about 1 ½ hours). To stimulate effort, we told all groups that 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), (2) Process variables, and (3) Outcome variables (dependent variables). (We also collected information on problem solving style and computer and Excel efficiency and found no important differences between experimental groups.) Below, we describe these variables and their measurement.

Experimental factors: We systematically manipulated two experimental factors:

1. **DSS Availability.** (Yes -- 1 or No -- 0) for the two DSS used, namely, Syntex and ABB.
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.

Process and Outcome variables: We summarize the measures for the process and outcome variables in Tables 2a and 2b. Wherever feasible, we used or adapted scales from previous research. However, for several constructs, we had to develop new measures because well-tested scales either did not exist, or did not specifically measure the constructs of interest for this study. A few of the items listed in Table 2 need additional description.

Insert Tables 2a and 2b about here

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 response model that we could use as a scoring rule to determine what the incremental return would be for *any* recommendation made by the subject. Thus, Incremental Return can be viewed as the most likely profit or revenue that a group's recommendation would have generated when implemented:

ABB: For ABB we used the market results reported in Gensch et al. (1990, Table 2, p. 16):

- No impact of additional effort deployed on customers who are considered to be loyal to ABB or loyal to competitors. Specifically, if either ABB or a competitor had a purchase likelihood statistically significantly higher than the closest competitor, ABB saw no gain in targeting these customers.
- 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 then would see a 30% gain on average from targeting these customers (called *switchables*).
- 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 then would see a 31% gain on average from targeting these customers (called *competitives*).

We used the choice probabilities to identify the largest 20 of the vulnerable customers (switchables and competitives). We then computed the expected incremental sales from each targeted switchable or competitive as:

$$\begin{cases} \text{Adjustment factor*(1- P(Buying from ABB))*Max Sales Potential,} \\ \qquad \text{if switchable or competitive customer} \end{cases}$$

0 otherwise

We computed the adjustment factor (=0.40) to give the overall sales increases from switchables and competitives of 30.5% to be consistent with the actual results that ABB realized.

Syntex: 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:

Profit for Product i =

[Base Sales$_i$ × Response$_i$ ($\frac{X_i}{Base\ X_i}$) × Margin i] – [X_i × Salesman Unit Cost], where

X_i is the salesforce effort level deployed on product i, and

Response$_i$ ($\frac{X_i}{Base\ X_i}$) 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 x 96.8 reps), then, from Row 9 of Figure 3, we get:

Naprosyn Profit = \$214,400,000 × 1.26 x 0.70 - \$63,000 × 145 = \$179, 965,000

Note that the DSS automates the estimation of the response function and invokes Excel's Solver optimization function 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). The DSS also permits the user to impose upper or lower limits on overall sales force spending or on spending on individual products.

<u>De-anchoring (departure from anchor point)</u>: In the case descriptions, we included clearly defined anchor points for the decision. We operationalized the anchor points as follows:

ABB: A senior district sales force manager makes the following recommendation in the case, "Our goal is to grow the company by landing more big contracts. You've got to fish where the big fish are, so the answer is easy. Let's pick the 20 biggest contract-proposals and go after those folks with the new program. If we can get a few more of those big fish to bite, Elwing [the President] and the board will be really happy!"

Syntex: The case describes the current management plan: Robert Nelson, the VP for Sales says, "Don't change a winning game plan." The current plan called for maintaining the same allocation (as specified in the "Base Selling Effort" column of Figure 4).

We determine departures from anchor points as follows. For ABB we computed de-anchoring as the lack of overlap between the set of twenty firms with the largest Purchase Volume and the set of twenty firms recommended by the subjects (20-number of firms overlapping). For example, if the recommended firms are the twenty largest firms, then de-anchoring is equal to 0 (20 – 20). If there are five firms targeted by the subjects that belong to the set of the twenty largest firms, then de-anchoring is 15 (20 – 5). For Syntex, we computed the deviation of the proposed effort allocation from that of the current allocation (the Euclidean distance of the allocation vector across the seven products from the anchor as shown in Table 4a and 4b). The major driver of profit in the Syntex case is the percent of effort allocated to one drug, Naprosyn, so de-anchoring in favor of Naprosyn is a key driver of model-predicted profits.

Expert rater's evaluations: All subjects completed a recommendation form for each case along with their justifications for their recommendations. We transcribed and typed these recommendation forms (to make them of uniform appearance) and gave them to three expert raters for evaluation. We also removed references to the form of DSS that the respondents had available so that the raters would not know if the respondent had access to a model 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 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 recommendation on a scale of 1-100. In a sense, the expert ratings represent another independent measure of decision quality.

4. Results

We now describe the results from our experiment.

Insert Tables 3, 4, 5 about here

The impact of DSSs on objective and subjective outcomes

We start by testing H1. The results in Tables 3 and 4a show that for both ABB ($F=13.25$, $p=0.00$) and Syntex ($F=13.0$, $p=0.00$), model-aided groups got higher Incremental Return than unaided groups. Therefore, the availability of DSSs to aid decision-making improved objective outcomes (i.e., decision quality), for both DSSs.[1]

For subjective outcomes the results are subtle. Table 5 shows that, overall, subjects were more satisfied with their decisions in the ABB case than in the Syntex case (3.94 versus 3.16; $F=74.7$, $p=0.00$). In both cases, whereas the availability of a DSS increases decision satisfaction, the effect is only significant for Syntex (3.39 versus 2.01; $p < 0.013$). Subjects also felt they learned more from the ABB case than from the Syntex case (3.61 versus 3.33; $F=14.33$, $p=0.000$). For Syntex, there was no difference between DSS and no-DSS subjects on the learning dimension. In the ABB case, contrary to what we hypothesized, unaided subjects reported that they learned more than did the model-aided subjects ($F=2.79$, $p=0.098$). At the same time, subjects perceived the software (both with and without DSS availability) for the ABB case to be more useful than the software available with the Syntex case (4.23 versus 3.58; $F=24.2$, $p=0.00$). However, for ABB, DSS Availability did not significantly impact the perceived Usefulness of the software, whereas DSS Availability increased the perceived Usefulness of the tool in the case of Syntex ($F=10.98$, $p=0.001$). This is not surprising given that the Syntex DSS offered directional feedback to its users vis-à-vis the no-DSS spreadsheet.

[1] Note there is no obvious way to define a unique, objective, and valid measure of decision quality in resource allocation decisions. Without externally validated results from the use of a decision model, decision quality will be idiosyncratic to the goals pursued by a user. Even when the goal is unique and objective, a higher outcome on a goal may not necessarily signify improved strategic benefits when taking into account all aspects of a decision context. We have circumvented these types of problems by using award-winning models that have been shown to result in superior outcomes in actual use in the context described. We also note that subjective performance measures, such as Satisfaction, that pertain to subjects' confidence in their recommendation need not correlate highly with objective indicators of performance (e.g., incremental return, de-anchoring). However, in our context, we can be reasonably confident that a significant positive effect of DSS availability (Table 5) directionally indicates a positive effect on objective measures of decision quality. These observations underscore the need for testing a DSS in actual use to determine if it improves objective measures of performance before deploying it widely.

We note here that it might be difficult to discern the effect of DSS on subjective performance measures, as reported by the decision-makers themselves. Studies on judgment accuracy have indicated that individuals are not very good at recognizing what they know (Heath and Gonzales 1994; Alba and Hutchinson 2000). For example, individuals' expressed confidence in their judgments is greater than what it should be, based on their performance. Possible causes for this "overconfidence" might be that people are insufficiently critical of their own inference processes, or their lack of attention to the situation.

In terms of Expert Ratings of the decisions, overall the experts gave higher scores to the ABB recommendations than to the Syntex recommendations (56.4 versus 48.9; F=11.5, p=0.001); however, we do not find support for H1, because in neither case were the experts able to directly detect a difference between DSS-aided and unaided groups. To gain a better understanding of the reasons for this unexpected result, we ran a number of exploratory regression analyses, regressing Expert Ratings against different explanatory variables. We found that the *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. That is, the more detailed the explanation for a recommendation, the better the raters evaluated that recommendation.

Recall that the experts only saw the reports that the teams produced, i.e., the recommended additional number of salespeople for each of the seven products for Syntex and the selection of the twenty customers to be targeted for ABB, along with their written justifications for the recommendations. We hypothesize that in the absence of objective performance indicators, expert raters may employ potentially biasing cues, such as the length of the report, in making an assessment of the quality of the recommendations. To test 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 De-anchoring -- that may or may not be associated with actual decision quality. Table 6a 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 6b. Our analyses suggest that there is an underlying trait, namely, the tendency to write long reports, that is not only distinct from group performance (Table 6b) but is also the main driver for Report Length (ABB: $\hat{b}$ = 0.52, Syntex: $\hat{b}$ =0.52). Thus, using report length as a primary cue leads to a judgmental bias on the part of the expert raters.

Insert Tables 6a and 6b here

There are some interesting differences between the ABB and Syntex cases on expert evaluations. For ABB, Report length was the only significant cue. For Syntex both cues -- the extent of De-anchoring and Report Length -- were highly significant, with the latter having considerably more influence (β=0.73) than the former (β=0.22). Thus, the use of a DSS for Syntex leads to more de-anchoring (Table 4a) and also shorter reports (β = -0.36, Table 6b), leaving the net effect of DSS on Expert Ratings indeterminate, in spite of the fact that DSS Availability leads to higher Incremental Return (Table 4a).

In summary, our results support H1 regarding objective outcomes. When considering subjective outcomes, our results offer only mixed support for H1. Learning seems to be lower with DSS Availability in the case of ABB, but Satisfaction and Perceived Usefulness are higher with DSS Availability in the case of Syntex. And it appears that the main (and biased) cue that expert raters use to determine decision quality is the length of the report supporting the recommendation.

The impact of DSSs on decision process variables

H2 hypothesizes that a DSS will improve several elements of the *decision process*. As summarized in Table 2b, we measured five process variables.

(1) Process Complexity. Overall, subjects perceived the Syntex case to be more complex than the ABB case (3.94 versus 3.55; F=21.8, p=0.00). For both cases, the DSS Availability had a significant direct effect in reducing perceived process complexity (Table 5).

(2) Cognitive Effort. Overall, subjects reported spending more effort on the ABB case than on the Syntex case (4.32 versus 4.12; F=12.9, p=0.00). There were no direct effects of DSS Availability

on cognitive effort in the case of ABB. However, for Syntex, DSS Availability marginally ($p < 0.105$) increased the amount of cognitive effort devoted to the task. (Table 5).

(3) Discussion Quality. Overall, subjects reported higher quality discussion during the ABB case than during the Syntex case (4.29 versus 3.92; $F=36.88$, $p=0.000$). DSS Availability did not affect discussion quality in the ABB case, but for the Syntex case, DSS Availability significantly improved the quality of discussions between the team members (Table 5).

(4) Number of Decision Alternatives Generated. There was no difference in the number of decision alternatives generated in the two cases. Further, DSS Availability had no impact on this variable (Table 5).

(5) De-anchoring. For both the ABB and the Syntex cases, DSS Availability led to significant de-anchoring. In ABB (Table 3), subjects with DSS moved farther away from the current practice of focusing on large customers, and focused more on smaller (average sales volume of $45,306K versus $28,145 for the unaided groups) customers. In Syntex (Table 4), the subjects recommended a larger sales force size and more effort allocation to Naprosyn than according to the current plan.

Overall, we find partial support for H2, in that DSS Availability affects the objective process measure (subjects move farther away from anchor points). However, DSS Availability has only limited effects on subjective process measures (considering only main effects). To learn more about the decision-making process, we also conducted a series of path analyses using LISREL 8.30 (Figures 5 and 6). The effects of DSS Availability in both the ABB and the Syntex case were estimated simultaneously in one model. This approach made it possible to compare the effects for the two cases. The paths between ABB and Syntex process variables and between ABB and Syntex outcome variables reflect the fact that we should expect within-subjects correlations among these variables. We analyzed how the four outcome variables are influenced by the process variables and the treatment variable (DSS Availability), after controlling for order effects. We performed four separate analyses (one analysis per outcome variable). Table 7 contains the results of these analyses[2].

Insert Figures 5 and 6 and Table 7 about here

DSS Availability increases De-Anchoring, an objective process measure, re-affirming the main effects of DSS on de-anchoring (Tables 3 and 4). However, DSS Availability has only limited effects on subjective process measures: it reduces perceived process complexity and increases Discussion Quality (Syntex only). Because DSSs are informational and structural aids, we should expect that an award-winning DSS would reduce the degree of perceived complexity (Table 7, $\hat{b}$ = -0.20 for both ABB and Syntex). Interestingly, while this reduction in Process Complexity means that ABB users tend to decrease their cognitive effort (Table 5: mean value of 4.40 for unaided vs. 4.24 aided subjects) and thus do not experience a higher level of Discussion Quality than their unaided counterparts (Table 5, F=0.44, p=0.507), Syntex users deploy more Cognitive Effort, which, through the indirect effect of the decision process (Table 7, $\hat{b}$ = 0.40, t=4.40) leads to a significant increase in perceived Discussion Quality (Table 5: F = 4.03, p = 0.047). In other words, users of the ABB DSS are able to save effort through the reduction in complexity (no direct effect of DSS on Cognitive Effort (Table 7: $\hat{b}$ = -0.09, t = -1.16), whereas the Syntex DSS directly stimulates users to expend more cognitive effort (Table 7: $\hat{b}$ = 0.15, t = 2.06). The additional effort gets re-invested and Discussion Quality – which is a key process difference between ABB and Syntex – improves.

[2] We performed all path analyses using individual level data although some variables were measured at the dyadic level (e.g., profit). Although there might be dependencies between group members, the complexity of our model structure (simultaneous estimation of process and outcome variables) and the relatively small sample sizes precluded our using more advanced multi-level models. We also note that most of the subjective process and outcome variables exhibited substantial within-group variation, thus reducing the likelihood of dependencies in the individual-level data.

In sum, our analysis supports H2 with respect to Syntex, but not with respect to ABB. For both cases, however, DSS Availability does influence the objective De-anchoring measure. *The impact of process on outcome variables*

Next we test H3. As hypothesized, the process seems to impact outcome variables, especially subjective outcomes. Subjects who find the decision process to be more complex realize lower objective Incremental Return in ABB ($\hat{b}$ =-0.15, t=-1.87). For Syntex , this result is directionally the same, but the coefficient is not significant. De-anchoring has a significant effect on Incremental Return, but the directionality of the effects is different for the two cases ($\hat{b}$ = -0.58, t=-5.92 for ABB and $\hat{b}$ =0.36, t=4.52 for Syntex). Thus, it appears that while subjects with a DSS move farther away from anchor points than those without, ABB subjects moved away in a direction that did not help them achieve a higher objective outcome. For both ABB and Syntex, subjects reporting higher levels of Discussion Quality also report higher levels of Satisfaction, Learning, and Perceived Usefulness of the exercise. or both ABB and Syntex, when subjects find the decision process to be more complex, they are less satisfied but learn more[3] In the case of ABB, the subjects who believed they put in more cognitive effort were also more satisfied with the outcome.

In sum, our results provide general support for H3, i.e., the process itself has the potential to change outcomes. (This is not the case for ABB, because, as we saw in our discussion of H2, the process did not improve for the DSS subjects as compared to the non-DSS subjects.) While the

[3] In our study, DSS Availability does not enhance perceived learning and for ABB, it decreases perceived learning. Learning appears to be a function of process complexity and discussion quality. Subjects perceive that they learn more when they perceived the quality of the discussions to be good (Table 7: ABB: $\hat{b}$ = 0.35, t=4.19, Syntex: $\hat{b}$ = 0.29, t= 3.35) and also when they believe the process to be more complex (Table 7: ABB: $\hat{b}$ = -0.25, t=4.41, Syntex: $\hat{b}$ = -0.24, t= 1.88). Since DSSs, through their design, try to reduce process complexity, it is not surprising that the use of a DSS does not improve perceived learning overall.

negative impact of De-anchoring on Incremental Profit in the case of ABB may seem surprising, note that De-anchoring need not necessarily lead to better performance; the benefits of de-anchoring depends on the quality and design of the DSS, a point we elaborate on below.

Differences in Effects between ABB and Syntex models

The Experimental Factor rows in Table 7 shows the direct impact of DSS Availability. Overall, the direct effect of DSS Availability on Incremental Return is higher for ABB ($\hat{b}$ = 0.60) than for Syntex ($\hat{b}$ = 0.32). In Table 8, we split the total effects of DSS Availability on outcomes as direct and indirect (through the decision process) effects. We see that DSS Availability has nearly the same total impact in terms of Incremental Return for ABB ($\hat{b}$ = 0.42) and Syntex ($\hat{b}$ = 0.47). However, in the case of ABB, the decision process has an overall negative effect on Incremental Return, whereas for Syntex, the decision process has a significant positive effect on Incremental Return.

To formally test H4, we first tested for the overall equivalence of the path models of ABB and Syntex (i.e., all coefficients are constrained to be equal for the two cases. Even a perfunctory scan of Table 7 suggests that there are several coefficient differences between the ABB and Syntex models. Thus, it is not surprising that H4 is rejected as summarized in the Table below:

Outcome	Unconstrained	Equality constrained
Incremental Return	$\chi^2(30) = 34.73$	$\chi^2(57) = 104.37$ Difference ($p < 0.01$)
Satisfaction	$\chi^2(30) = 38.87$	$\chi^2(57) = 86.70$ Difference ($p < 0.01$)
Learning	$\chi^2(30) = 38.37$	$\chi^2(57) = 44.36$ Difference ($p < 0.02$)
Perceived Usefulness	$\chi^2(30) = 37.00$	$\chi^2(57) = 84.20$ Difference ($p < 0.01$)

A primary reason for the rejection of H4 in the case of Incremental Return is the functional relationship between De-anchoring and Incremental return, as is evident even in the correlation coefficients between these variables (ABB = -0.22 vs. Syntex = 0.52). Thus, something in the structure of the ABB case causes de-anchoring in the wrong direction (with respect to incremental return), and something in the structure of Syntex causes de-anchoring in the right direction. We elaborate further on this difference in the discussion Section.

Next, we examined the coefficients of the ABB and Syntex models for any systematic patterns of coefficients. We notice the following: For Syntex, the inter-relationships between the process variables appear to be stronger. Specifically, Process Complexity has a stronger positive effect on Cognitive Effort ($\hat{b}$ = 0.40, t=4.40 versus $\hat{b}$ = 0.31, t=3.23); Cognitive Effort seems to have a stronger positive impact on Discussion Quality ($\hat{b}$ =0.41, t= 4.22 versus $\hat{b}$ = 0.36, t=3.91); Cognitive Effort seems to have a stronger positive effect on Decision Alternatives ($\hat{b}$ =0.32, t=3.41 versus $\hat{b}$ =0.17, t=1.66); and finally, Discussion Quality seems to have a stronger positive effect on Decision Alternatives ($\hat{b}$ = 0.35; t=3.96 versus $\hat{b}$ = 0.26, t=2.71). To formally test whether the process inter-relationships are stronger for Syntex, we compared the unconstrained model against a model in which the significant parameters in the upper triangular matrix of Table 7 were equal for Syntex and ABB. The test, however, reveals that this pattern is not statistically significant, possibly due to our small sample sizes. Nevertheless, future research might reveal systematic process patterns do exist across different DSS.

Effects of Order variable: Doing the ABB case after Syntex (Order = 1) reduces Process Complexity associated with the ABB case ($\hat{b}$ =-21, t=-2.28), enhances Discussion Quality during the ABB case ($\hat{b}$ =0.16, t=1.80), and decreases Decision Alternatives in the Syntex case ($\hat{b}$ =-0.14, t=-1.72). These results are consistent with the subjects' perception of overall higher process complexity of Syntex (Table 5).

In sum, H4 is rejected, even though there is a large degree of similarity[4] in the patterns of the significant coefficients for both the ABB and Syntex models.

[4] ABB and Syntex DSS have similar effects in "form," but not necessarily in content and scale. For example, we find that their indirect process effects are alike (Table 8). We also find support for the structural process model (especially with respect to the subjective measures: complexity/cognitive effort/discussion quality, decision alternatives (Table 7 and Figure 5)). Moreover, the relationship between subjective and objective performance measures are alike: they do not correlate well with each other. Finally, the test of equality of coefficients capturing

5. Discussion and Conclusion

Our results show that decision models for marketing resource allocation do improve objective outcomes, primarily because of the intrinsic quality of a DSS and through its ability to de-anchor users from their a priori predilections. This finding is not surprising because we used award-winning models that have had a favorable impact on actual outcomes in practice. However, DSS effects on subjective perceptions of achieved outcomes were mixed. For ABB, DSS did not increase satisfaction with the outcome, perceived usefulness of the model, or expert rater's assessments. For Syntex, DSS use did enhance perceived satisfaction with the outcome and perceived usefulness of the model. Even though DSSs reduced subjects' perception of Problem Complexity, they had no impact on perceived Learning (it even appears that there could a reduction in perceived learning with the use of a DSS). By investigating the effects of the decision process, separate from the direct effects of DSS Availability, we found a disconnect between subjective and objective effort and performance measures for both cases: DSS availability did not directly increase subject's subjective outcomes (Satisfaction, Learning, Usefulness). However, the subjective outcomes were influenced primarily by Discussion Quality and Perceived Complexity of the task. Given that Discussion Quality is a key process variable that enhances perceived outcomes, future research should flesh out how specifically discussion quality enhances team interaction and its effects on perceived outcomes of DSS use.

The mixed results with respect to subjective and objective outcomes also offer insights about why DSS use for tasks such as resource allocation is not more widespread. Simply promising improved objective outcomes by using a DSS is not enough – DSS design enhancements must give users cues to help them perceive that improved outcomes are likely to occur with DSS use. It is also surprising that experts had difficulty evaluating the quality of a subject's recommendations by looking only at those recommendations and the associated supporting explanations. This evaluation mirrors the typical situation faced by top managers when they receive reports and recommendations without observing the decision process or tools used to help generate those recommendations. Therefore, our results suggest that senior management may find it challenging to distinguish between DSS-supported recommendations

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the effects of the process variables was not rejected.

(which our research suggests are superior) and non-DSS supported recommendations, especially when potentially biasing cues (e.g., length, format of the presentation) are present and well-supported expected performance indicators are lacking. And, if DSSs generate a cost for the organization without a perceived benefit (lack of improved perceived decision quality) they are unlikely to be widely used, even when their use is actually likely to be beneficial. Our study also shows that DSS can help reduce the perceived cognitive complexity of a resource allocation task. Thus, use of DSS is more likely when the resource allocation problem is intrinsically complex (e.g., finding optimal prices and seat allocations across a large number of flight segments).

Our rejection of H4 led us to investigate the differences between the ABB and Syntex DSSs and contexts in more depth. We note that the DSS for ABB is non-directive (i.e., it gives no feedback or makes specific recommendations) whereas the Syntex DSS provides both a specific recommendation and a projected profit impact of that recommendation relative to the current allocation. Our post-experimental questionnaire supports our observation that this form of feedback from the Syntex model 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" was statistically significantly different between DSS and non DSS groups while it was not different for the ABB case-groups. Goodman (1998) and Wigton et al (1986) show that feedback can play both an informational role (promoting knowledge acquisition) as well as a motivational role (providing a reward-cue for increase cognitive effort investment). In the framework of Balzer et al. (1989), user interactions with the Syntex DSS -- but not with the ABB DSS-- provides "cognitive feedback" that informs about the task and the relations in the task environment.[5] Balzer's et al's. (1989) literature review shows that this task information feedback is the component of cognitive feedback that has the most significant effect on performance.

While our results clearly suggest the need for further research on the role of feedback, based on our study, we make the following initial recommendations for DSS design:

[5] The Syntex DSS allows its users to conduct "what-if" analyses by experimenting with different constraints and observing their impact on expected profits, whereas the ABB DSS runs on static input data and is usually run only once. Thus, the ABB DSS merely offers its users additional information in terms of computed choice probabilities, but does not have built in options to encourage users to experiment with choice criteria or explore the profit consequences of alternate targeting plans.

(1) Design DSSs to encourage discussion. Although designing DSSs that lead to improved objective outcomes should always be the primary criterion, that alone is not enough to encourage use of the DSS, or help users feel good about DSS use. It is important to design features that encourage interaction with the DSS, provide explanations for recommendations, generate visual outputs, all of which can facilitate managerial discussion about the decision problem and improve perceived outcomes (satisfaction, learning, and usefulness of the DSS).

(2) 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 more likely to use systems that they understand and trust, so the operation and the logic of the DSS must be clear. And explanations for the DSS recommendation should be sufficiently complete so that DSS users are able to generate the appropriate support for their recommendations.

(3) Design for Effort Reduction and Consideration of Multiple Alternatives. When the DSS reduces process complexity and facilitates the assessment of multiple alternatives, decision quality improves: There is greater de-anchoring when the DSS can directly induce consideration of more alternatives (through its problem representation and design), and also indirectly increase consideration of alternatives by reducing perceived process complexity.

The above approaches to designing DSS alone are not enough. Other factors, such as ease of use, compatibility with existing systems, etc. that have been identified in the literature are also required to increase the intent to adopt (Rogers, 1995).

This research has several limitations, which suggest further research questions. It is based on a laboratory experiment, with limited duration, and without all the political complexities associated with DSS use in organizational settings. While our design enhances the internal validity of our results, its external validity is subject to question. 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 work. These issues suggest the need for field research (preferably using experimental techniques such as random assignment) in the context of the introduction of a DSS in real organizations.

Our analysis framework is new. While we have used an approach based on the literature to develop structural equation models for analyzing the decision process, this framework should be tested in other contexts, perhaps including ethnographic research to get a richer picture of the decision making process. Also, our conjecture on the role of feedback should be tested using both feedback and non-feedback versions of the same DSS.

Finally, the theoretical foundations of the field of DSS design and effectiveness could be further enhanced and strengthened. There are many rich research opportunities associated with developing generalizations about what works in this domain and why. And while such generalizations will be important for theory, they also have the potential to have a major impact on improving the practice of DSS design and implementation.

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Table 1: Summary of major studies of DSS effectiveness

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	O/P *	Key Results/Comments
Fudge and Lodish (1977)	Evaluate the effectiveness of a DSS (Decision Calculus model)	Allocation of sales effort at Air cargo services of United Airlines	Field	Availability of the CALLPLAN DSS, including training	*Objective:* Sales	O	After six months, salespeople who used a DSS had significantly higher sales (+8% on average). DSS users viewed the system as productive.
Chakravarti, Mitchell, and Staelin (1979)	Evaluate effectiveness of a DSS (Decision Calculus model)	Allocation of ad budget over several periods (includes carry-over effects)	Lab	Availability of the ADBUDG DSS	*Objective:* Profits; Accuracy of parameter estimates of underlying model	O	Subjects made better decisions before being exposed to the DSS. System use did not lead to improved estimates of parameters (but the simulated dynamic environment seems to be overly complex).
McIntyre (1982)	Evaluate effectiveness of a DSS (Decision Calculus model)	Allocation of ad budget over several periods (no carry-over effects); sales prediction	Lab	Availability of the CALLPLAN DSS; Task characteristics (size of the problem, noise-to-signal ratio in market): Characteristics of decision makers	*Objective:* Profits; Accuracy in predicting sales; Stability *Subjective:* Confidence in decision	O	DSS users achieved higher profit levels with less volatility, but they did not do better in predicting sales levels. There was no difference in the perceptions between model users and non-users that the allocations result in profits near to optimal profits. However, decision makers felt more confident when using the DSS.
Aldag and Power (1986)	Evaluate DSS effectiveness	Strategic management decision task	Lab	Availability of DSS; Characteristics of decision makers	*Subjective:* Attitude toward process and outcome (e.g., confidence, satisfaction)	O/P	DSS availability did not improve performance of decision (based on evaluations of 3 raters). Limited support for improved subjects' attitudes toward the decision process and solution.
Lodish, Curtis, Ness, and Simpson (1988)	Assess effectiveness of a DSS (Decision Calculus model)	Allocation and sizing of sales force (Syntex Laboratories Inc.)	Case study	Actual implementation of DSS (CALLPLAN) in a company.	*Objective:* Sales/Gross Margin	O	DSS helped Syntex decide to significantly increase its salesforce size and to change its effort allocation to products and market segments. This decision resulted in a documented continuing $25 million - 8% -yearly sales increase.

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	O/P *	Key Results/Comments
Gensch, Aresa, and Moore (1990)	Assess effectiveness of a DSS (multi-attribute disaggregate choice model) for segmentation and targeting	Allocation of marketing effort based on model predictions with respect to choice among suppliers of ABB Electric Inc.	Case study	Actual implementation of DSS (multi-attribute disaggregate choice model) in a company.	*Objective:* Sales	O	ABB used the model-to segment and target customers. After a year of implementation, total transformer sales for the industry were down 15%. In contrast, ABB sales in the 2 districts using the DSS increased (18% and 12%), whereas its sales in the territory not using the DSS methods were down 10%. The management at ABB Electric felt that the DSS was a competitive advantage that led them to grow market share from 4% to over 40% over a fifteen year period along with increased profitability in a highly competitive market.
Sainfort, Gustafson, Bosworth, and Hawkins (1990)	Evaluate DSS effectiveness	Conflict resolution (various dyadic real-life problems between couples)	Lab	Availability of DSS and video (vs. no aid of any kind). DSS provided support for structuring the process and included database access and alternative evaluation; Video showed how to deal with conflict.	*Subjective:* Perceived quality of process and problem resolution	O/P	DSS led to a higher number of alternatives generated than Video and greater perceived progress in resolution of the problem a month later. DSS and Video performed no different (but better than control) on perceived problem understanding and decrease in level of frustration with problem. No effect of DSS or Video on the quality of alternatives generated.
Todd and Benbasat (1992)	Evaluate DSS effects on effort minimization	Choice of an alternative from a set of alternatives, all described by a set of attributes	Lab	Availability of DSS	*Objective*: Cognitive effort (extent of information use based on protocol analysis)	P	Aided subjects did not use more information than those without one. The subjects behaved as if effort minimization was an important consideration, i.e., the subjects make a tradeoff between improving decision quality (taking advantage of expanded DSS processing capabilities) and conserving effort.
Guimaraes, Igbaria, and Lu (1992)	Identify DSS success factors	N/A	Survey	Characteristics of DSS, decision makers, and task	*Subjective:* DSS success (satisfaction and perceived benefits)	O	DSS success was found positively related to user participation in DSS development, user training, top management support, as well as task characteristics (more structure, less difficulty) and DSS characteristics (lower level control rather than strategic planning).

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	O/P *	Key Results/Comments
Davis and Kottemann (1994)	Assess user perceptions of the effectiveness of what-if analysis relative to unaided decision making and quantitative decision rules	Production planning task	Lab	Availability of DSS (what-if model)	*Objective*: Performance *Subjective:* Perceived performance; Perceived DSS effectiveness	O	Subjects perceived performance differences where none existed, and did not detect large differences when they were present. What-if analysis creates an illusion of control.
Gundersen, Davis, and Davis (1995)	Evaluate the effectiveness of a Group DSS	Consensus on human resource task (candidate selection for promotion)	Lab	Availability of Group DSS (Analytical Hierarchy Process)	*Subjective:* Satisfaction with process, confidence in solution	O	Aided and unaided groups' promotional choices differed significantly. Aided groups required more time to reach a consensus. Aided subjects reported higher satisfaction with process, but no difference in confidence, or in commitment to group decision.
Vandenbosch and Higgins (1995)	Assessm the impact of DSS effectiveness from a learning perspective	N/A	Survey	Characteristics of Executive Support Systems (quality, ease of use, analysis capability), decision makers (training, computer self-efficacy)	*Subjective:* Perceived competitive performance, two kinds of learning (mental model maintenance and building)	O	The executives' perception of competitive performance resulting from the DSS use was strongly linked to mental-model building (measured as the perceived DSS usefulness for improving insights and creativity as well as for testing assumptions). However, it was not linked to mental model maintenance (measured as DSS usefulness for understanding the business and increasing focus). Ease of use and the quality (informational value) of the DSS are necessary conditions to learning; analysis capability primarily aids mental model building.
Hoch and Schkade (1996)	Evaluate DSS effectiveness in combination with experience (pattern matching efforts)	Forecasting of credit ratings	Lab	Availability of DSS (linear model); Availability of database support (pattern matching support); High/low predictability of environment (credit rating)	*Objective:* Accuracy of forecasting performance	O	In high predictability environment, aided users did better, but not significantly better than unaided users. In the low predictability environment, users with database support (pattern matching) did significantly worse than model only or unaided. Users with DSS and database support did best.

Study	Purpose	Decision Supported	Study Type	Explanatory Variables	Outcome (O) and Process (P) Measures	O/P *	Key Results/Comments
Van Bruggen, Smidts, and Wierenga (1996, 1998)	Assess the impact of differences in DSS quality	Marketing mix decisions in the MARK-STRAT simulation environment.	Lab	Availability of DSS (what-if model for sales and market share predictions) High/low DSS quality (i.e., the prediction precision) High/low time-pressure	*Objective:* Profit De-anchoring *Subjective:* Perceived usefulness, Decision confidence	O/P	DSS users achieved higher profits than non-users. Although users of high-quality DSS outperformed users of lower quality DSS, there was no significant difference in perceived usefulness or decision confidence. DSS users were less susceptible to applying the anchoring and adjustment heuristic and, therefore, showed more variation in their decisions in a dynamic environment. Low-analytic subjects and subjects operating under low time pressure benefited most from a DSS.
Present Study	Assess how DSSs influence decisions	Two different resource allocation tasks: Salesforce allocation (see Lodish et al. 1988) and target segment selection (see Gensch et al. 1990)	Lab	Availability of DSS Task order	*Objective:* Incremental return (profit or sales) Extent of de-anchoring Expert ratings *Subjective:* Complexity, Cognitive effort, Satisfaction, Discussion Quality, Learning, etc.	O/P	DSS use improves objective decision outcomes for both DSS models. However, DSS users often do not report better perceptions of outcomes. Expert evaluators had difficulty detecting objective decision quality. Effects of DSS on both process and outcomes may be context and DSS-design specific, with DSSs that provide specific feedback having stronger effects both on the process and on the outcomes.

* O = Outcome measures, P = Process measures as per our framework (cf. Figure 6).

Table 2a: Summary of outcome variables and measures

Construct	Description	ABB	Syntex
Incremental Return	Estimated incremental sales (ABB) or incremental profit (Syntex) associated with a recommended course of action.	Mean = 4,135	Mean = 260,638
Decision Satisfaction	5-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 = 3.94 Alpha =0.90	Mean = 3.16 Alpha = 0.94
Perceived Learning	3-item Likert scale (normalized 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 = 3.61 Alpha = 0.82	Mean = 3.33 Alpha = 0.86
Perceived Usefulness	3-item Likert scale (normalized 1 – 5) It enabled us to make decisions more quickly. It increased our productivity. It improved our performance.	Mean = 4.23 Alpha = 0.91	Mean = 3.59 Alpha = 0.96
Expert Rater's Evaluation	Single item overall judgment scale (1-100 scale)	Mean = 57.6	Mean = 48.9

Table 2b: Summary of process variables and measures

Construct	**Description**	**ABB**	**Syntex**
Process Complexity	<u>3-item Likert scale (normalized to 1 – 5)</u> It was a complex process. It was a challenging process. It was a difficult process.	Mean = 3.55 Alpha = 0.87	Mean = 3.94 Alpha = 0.91
Cognitive Effort	<u>3-item Likert scale (normalized to 1 – 5)</u> We were totally immersed in resolving this problem. We took this task seriously. We put in a lot of effort.	Mean = 4.32 Alpha = 0.73	Mean = 4.11 Alpha = 0.79
Discussion Quality	<u>3-item Likert scale (normalized to 1 – 5)</u> 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 = 4.29 Alpha = 0.58	Mean = 3.92 Alpha = 0.59
Decision Alternatives Generated	<u>2-item Likert scale (normalized to 1 – 5)</u> We had discussions about many decision alternatives that were not part of the final recommendation. We considered several alternatives carefully.	Mean = 3.51 Alpha = 0.56	Mean = 3.54 Alpha = 0.65
De-anchoring	Deviation of decision from anchor point (ABB: 20 – number of targeted firms that belong to the set of the 20 firms with the highest purchase volume; Syntex: Euclidean Distance from the base allocation)	Mean = 12.25	Mean = 155.76

Table 3: ABB – Resource allocation results

	Incremental Return ($000) Mean (Std. Dev.)	Number of "Switchable" Firms in Target Set Mean (Std. Dev.)	Purchase Volume of Targeted Firms ($000) Mean (Std. Dev.)	Extent of De-anchoring Mean (Std. Dev.)
Unaided Groups – (n = 28)	3,219 (1,945)	6.29(2.31)	45,306 (14,279)	11.18(3.38)
Model-aided Groups (n = 28)	5,052 (1,821)	12.82(3.66)	28,145 (8,243)	13.32(1.47)
	F(1,54) = 13.25 p = 0.001	F(1,54) = 63.84 p = 0.000	F(1,54) = 30.34 p = 0.000	F(1,54) = 9.48 p = 0.003
Anchor	4,911	6	70,087	0
Optimal	6,905	20	24,174	14

The table shows that the model-aided groups generated higher incremental revenue than unaided groups and also targeted smaller, but more responsive firms. Note that the Anchor represents the set of twenty firms with the largest sales potential. Six firms belong to both the anchor set and the optimal set of twenty "switchable" firms.

Table 4a: Syntex – Resource allocation results

	Incremental Return ($000) Mean (Std. Dev.)	Number of Salespeople added Mean (Std. Dev.)	Extent of De-anchoring (Euclidean distance) Mean (Std. Dev.)
Unaided Groups (n = 27)	252,918 (16,477)	175 (145)	116 (94)
Model-aided Groups (n = 28)	267,553 (13,535)	270 (150)	192 (95)
	$F(1,53) = 13.00$ $p = 0.001$	$F(1,53) = 5.77$ $p = 0.020$	$F(1,53) = 8.78$ $p = 0.005$
Anchor (Base Allocation)	218,827	0	0
Current Management Plan	241,053	120	54
Optimal	276,433	315	228

This table shows that the model-aided group generated higher incremental return (expected profit) and recommended a larger sales force than the unaided group. For both groups the average recommendation of sales force size as well as the amount of de-anchoring (measured as the Euclidean distance from the base allocation) exceed management's current plan of sales force expansion. The Optimal plan is determined by doing an unconstrained optimization (without constraints on sales force size).

One group was identified as an outlier (recommended 1468 salespeople to be added) and dropped from the analysis.

Table 4b: Allocation across products (proportion of total number of reps)

	(Base and Current Plan)	Base / #Reps	Current Plan / #Reps	Optimal	/ #Reps	Unaided Groups (n=27) Mean (Std. Dev)	/ #Reps	Model-aided Groups (n=28) Mean (Std. Dev)	/ #Reps	Difference of aided vs. unaided groups Significance (F; p)
Naprosyn	0.23	/97	/124	0.43	/321	0.30 (0.09)	/186	0.38 (0.10)	/266	10.06; 0.00
Anaprox	0.33	/142	/182	0.23	/168	0.27 (0.08)	/160	0.25 (0.07)	/178	0.87; 0.36
Norinyl 135	0.12	/53	/67	0.10	/71	0.12 (0.02)	/72	0.11 (0.02)	/75	4.67; 0.04
Norinyl 150	0.06	/24	/31	0.05	/37	0.07 (0.04)	/39	0.05 (0.01)	/35	4.02; 0.05
Lidex	0.06	/27	/35	0.06	/47	0.07 (0.02)	/41	0.06 (0.01)	/43	2.03; 0.16
Synalar	0.07	/30	/38	0.04	/30	0.06 (0.01)	/35	0.05 (0.01)	/34	7.04; 0.01
Nasalide	0.13	/57	/73	0.09	/70	0.12 (0.04)	/74	0.10 (0.02)	/71	6.27; 0.02
TOTAL	1.00	430	550	1.00	744	1.00	606	1.00	702	

This table shows that relative to the unaided group the model-aided groups allocated a higher proportion of total effort to the more responsive product (Naprosyn) and cut back proportional effort on the other less responsive products.

Table 5: The Effect of DSS on subjective outcome and process variables

	ABB Case				Syntex Case			
	No DSS	DSS	Diff (F;p)	Total	No DSS	DSS	Diff (F,p)	Total
<u>Outcome Variables</u>								
Satisfaction	3.86 (0.84)	4.01 (0.68)	1.09; 0.299	3.94 (0.76)	2.91 (1.06)	3.39 (0.91)	**6.36**; 0.013	3.16 (1.01)
Learning	3.73 (0.83)	3.48 (0.72)	**2.79**; 0.098	3.61 (0.79)	3.32 (0.92)	3.35 (0.88)	0.04; 0.848	3.33 (0.90)
Usefulness	4.20 (0.78)	4.25 (0.77)	0.13; 0.724	4.23 (0.77)	3.20 (1.30)	3.96 (1.10)	**10.98**; 0.001	3.58 (1.26)
<u>Process Variables</u>								
Process Complexity	3.76 (0.81)	3.35 (0.81)	**6.99**; 0.009	3.55 (0.83)	4.09 (0.78)	3.79 (0.81)	**3.75**; 0.055	3.94 (0.85)
Cognitive Effort	4.40 (0.54)	4.24 (0.60)	2.19; 0.141	4.32 (0.57)	4.01 (0.75)	4.22 (0.57)	2.67; 0.105	4.12 (0.67)
Discussion Quality	4.26 (0.63)	4.32 (0.44)	0.44; 0.507	4.29 (0.54)	3.80 (0.68)	4.04 (0.55)	**4.03**; 0.047	3.92 (0.63)
Decision Alternatives	3.54 (1.00)	3.47 (0.74)	0.19; 0.668	3.51 (0.88)	3.53 (0.91)	3.55 (0.88)	0.03; 0.874	3.54 (0.89)

Standard deviation in ( )
Difference significant at 0.10 level in bold

Table 6a: Determinants of Expert Ratings (standardized regression coefficient, t-value in parentheses)

	Syntex Case	**ABB Case**
DSS Availability	0.11 (1.05)	-0.00 (-0.03)
Cue: Report Length[1)] Cue: De-Anchoring[1)]	**0.73 (7.85)** **0.22 (2.20)**	**0.52 (4.40)** 0.15 (1.16)
F R-Square	F(3,51) = 23.44 p = 0.00 0.58	F(3,52) = 7.22 p = 0.00 0.29

Table 6b: Determinants of Report Length (standardized regression coefficient, t-value in parentheses)

	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 R-Square	F(3,51) = 9.01 p = 0.00 0.35	F(2,52) = 2.23 p = 0.12 0.08	F(3,52) = 5.47 p = 0.00 0.24	F(2,53) = 0.14 p = 0.87 0.01

[1)] The factor Report Length is the number of words used in the group's recommendation for Syntex and ABB respectively. The factors De-Anchoring (Syntex only) and Report Length (both cases) were log-transformed.

[2)] To approximate the group 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.

Difference significant at 0.10 level in bold

Table 7: Path Analysis Results (standardized regression coefficient, t-value in parentheses)

	Outcome Variables				**Process Variables**				
	Incremental Return ABB Syntex	Satisfaction ABB Syntex	Learning ABB Syntex	Usefulness ABB Syntex	Process Complexity ABB Syntex	Cognitive Effort ABB Syntex	Discussion Quality ABB Syntex	Decision Alternatives ABB Syntex	De-Anchoring ABB Syntex
<u>Experimental Factors</u>									
DSS Availability									
ABB	**0.60 (7.28)**	0.06 (0.76)	-0.07 (-0.84)	0.03 (0.33)	**-0.20 (-2.50)**	-0.09 (-1.16)	0.13 (1.54)	0.00 (0.00)	**0.40 (4.60)**
Syntex	**0.32 (3.97)**	0.07 (0.81)	-0.06 (-0.67)	**0.15 (1.75)**	**-0.20 (-2.43)**	**0.15 (2.06)**	0.07 (0.76)	**-0.15 (-1.86)**	**0.37 (4.00)**
Order									
ABB	-0.04 (-0.51)	0.12 (1.47)	0.08 (1.03)	0.06 (0.61)	**-0.21 (-2.28)**	0.02 (0.19)	**0.16 (1.80)**	0.01 (0.08)	0.07 (0.77)
Syntex	0.04 (0.46)	-0.02 (-0.23)	0.10 (1.22)	-0.10 (-1.23)	-0.11 (-1.22)	0.14 (1.55)	-0.08 (-0.89)	**-0.14 (-1.72)**	-0.11 (-1.20)
<u>Process Variables</u>									
Process Complexity									
ABB	**-0.15 (-1.87)**	**-0.25 (-3.06)**	**0.35 (4.41)**	-0.06 (-0.63)		**0.31 (3.23)**	0.05 (0.51)	0.12 (1.23)	-0.05 (-0.51)
Syntex	-0.11 (-1.35)	**-0.24 (-2.76)**	**0.16 (1.88)**	**-0.25 (-2.80)**		**0.40 (4.40)**	-0.10 (-0.99)	-0.14 (-1.60)	-0.10 (-1.01)
Cognitive Effort									
ABB	0.11 (1.29)	**0.32 (3.74)**	0.11 (1.30)	0.04 (0.41)			**0.36 (3.91)**	0.17 (1.66)	0.15 (1.57)
Syntex	-0.07 (-0.73)	-0.00 (-0.05)	**0.19 (2.04)**	0.06 (0.61)			**0.41 (4.22)**	**0.32 (3.41)**	0.01 (0.06)
Discussion Quality									
ABB	0.07 (0.83)	**0.35 (4.19)**	**0.22 (2.74)**	**0.40 (4.08)**				**0.26 (2.71)**	0.04 (0.38)
Syntex	0.00 (0.01)	**0.34 (3.81)**	**0.29 (3.35)**	**0.44 (4.94)**				**0.35 (3.96)**	-0.01 (-0.08)
Decision Alternatives									
ABB	0.03 (0.41)	-0.02 (-0.25)	**0.14 (1.79)**	-0.09 (0.96)					0.13 (1.45)
Syntex	0.11 (1.30)	0.13 (1.57)	0.06 (0.62)	-0.02 (-0.22)					0.13 (1.28)
De-Anchoring									
ABB	**-0.48 (-5.92)**	-0.00 (-0.01)	-0.03 (-0.38)	0.00 (0.01)					
Syntex	**0.36 (4.52)**	-0.05 (-0.56)	0.01 (0.17)	0.07 (0.85)					

R-Square									
ABB	0.38	0.33	0.32	0.17					
Syntex	0.38	0.25	.0.25	0.34					
Chi-Square (df=30)	34.73 (p=0.25)	38.87 (p=0.13)	38.37 (p=0.14)	37.00 (p=0.18)					
CFI	0.98	0.97	0.97	0.97					

In this table we present the relationships of the path analyses. The data are standardized regression coefficients between the decision outcome and decision process variables (in the columns) and the experimental factors and decision process variables (the rows). Differences significant at the 0.10 level are shown in bold.

Table 8: The direct, indirect, and total impact of DSS Availability on decision outcomes (Standardized regression coefficient, t-value)

	Incremental Return		Satisfaction		Learning		Usefulness	
	ABB	SYNTEX	ABB	SYNTEX	ABB	SYNTEX	ABB	SYNTEX
Direct Effect of DSS Availability	**0.60 (7.28)**	**0.32 (3.97)**	0.06 (0.76)	0.07 (0.81)	-0.07 (-0.84)	-0.06 (-0.67)	0.03 (0.33)	**0.15 (1.75)**
Indirect Effect of DSS Availability (through the Decision Process)	**-0.17 (-2.99)**	**0.15 (2.81)**	0.02 (0.39)	**0.10 (1.71)**	-0.09 (-1.60)	0.02 (0.33)	0.03 (0.62)	**0.13 (2.21)**
Total Effect of DSS Availability	**0.42 (5.06)**	**0.47 (5.81)**	0.08 (1.01)	**0.17 (1.94)**	**-0.15 (-1.91)**	-0.04 (-0.47)	0.07 (0.72)	**0.29 (3.20)**
R-Square Model without Process Variables	0.17	0.23	0.05	0.02	0.02	0.01	0.02	0.10
R-Square Model with Process Variables	0.38	0.38	0.33	0.25	0.32	0.25	0.17	0.34

Difference significant at 0.10 level in bold

Figure 1: Sample of ABB Data, available to all groups

Customer Attitude & Choice Data (Basis)

Row	A	Customer ID	Purch. Vol.	District	Choice	Price	Energy_Loss	Maintenance	Warranty	Spare_Parts	Ease_Install	Prob_Solv	Quality
4	A	1	$761	1	0	6	6	7	6	6	5	7	5
5	B				1	6	6	6	7	9	9	7	5
6	C				0	6	5	7	5	3	4	7	6
7	D				0	5	5	6	7	8	2	6	5
8	A	2	$627	1	0	3	4	5	4	4	5	6	4
9	B				0	3	4	5	4	7	3	5	5
10	C				0	4	5	5	5	5	7	6	4
11	D				1	4	5	6	5	4	5	5	6
12	A	3	$643	2	1	6	6	7	7	6	7	7	6
13	B				0	5	6	7	7	5	6	8	6
14	C				0	5	6	7	5	5	8	6	5
15	D				0	6	5	5	4	2	8	6	5

‘

The four suppliers are A (ABB), B, C, and D. The variables were measured on a 1 – 9 scale, except for “Choice,” which represents the supplier chosen by the customer in the immediately prior purchase occasion.

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

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	A	B	C	D	E	F	G	H
1	Customer Demographics (Descriptors)							
2								
3		**Supplier**	**Pref. Supplier**					
4		**A: ABB**	18					
5		**B: GE**	23					
6		**C: Westingh.**	26					
7		**D: McGraw-E.**	21					
8		Sum	88					
9								
10	**Potential**	**RFQ Estimated**		**Firm**	**Consultant Recommended Target**			
11	**Customer**	**Purchase Vol. ($K**	**District**	**Chosen**	**A(ABB)**	**Supplier B**	**Supplier C**	**Supplier D**
12	**1**	$761	1	B	15.3%	82.3%	2.4%	0.0%
13	**2**	$627	1	D	0.0%	0.0%	2.6%	97.4%
14	**3**	$643	2	A	74.7%	25.3%	0.0%	0.0%
15	**4**	$562	3	D	48.8%	39.7%	0.0%	11.5%
16	**5**	$469	3	C	2.0%	0.0%	98.0%	0.0%
17	**6**	$233	1	B	0.0%	96.8%	3.1%	0.0%
18	**7**	$664	3	D	40.5%	7.7%	0.1%	51.8%
19	**8**	$767	3	D	0.0%	56.4%	0.0%	43.6%
20	**9**	$467	1	D	0.3%	0.0%	1.3%	98.4%

The model supported groups could run an 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 data, available to all groups

Product Model

Unit Cost of Salesperson $ 63

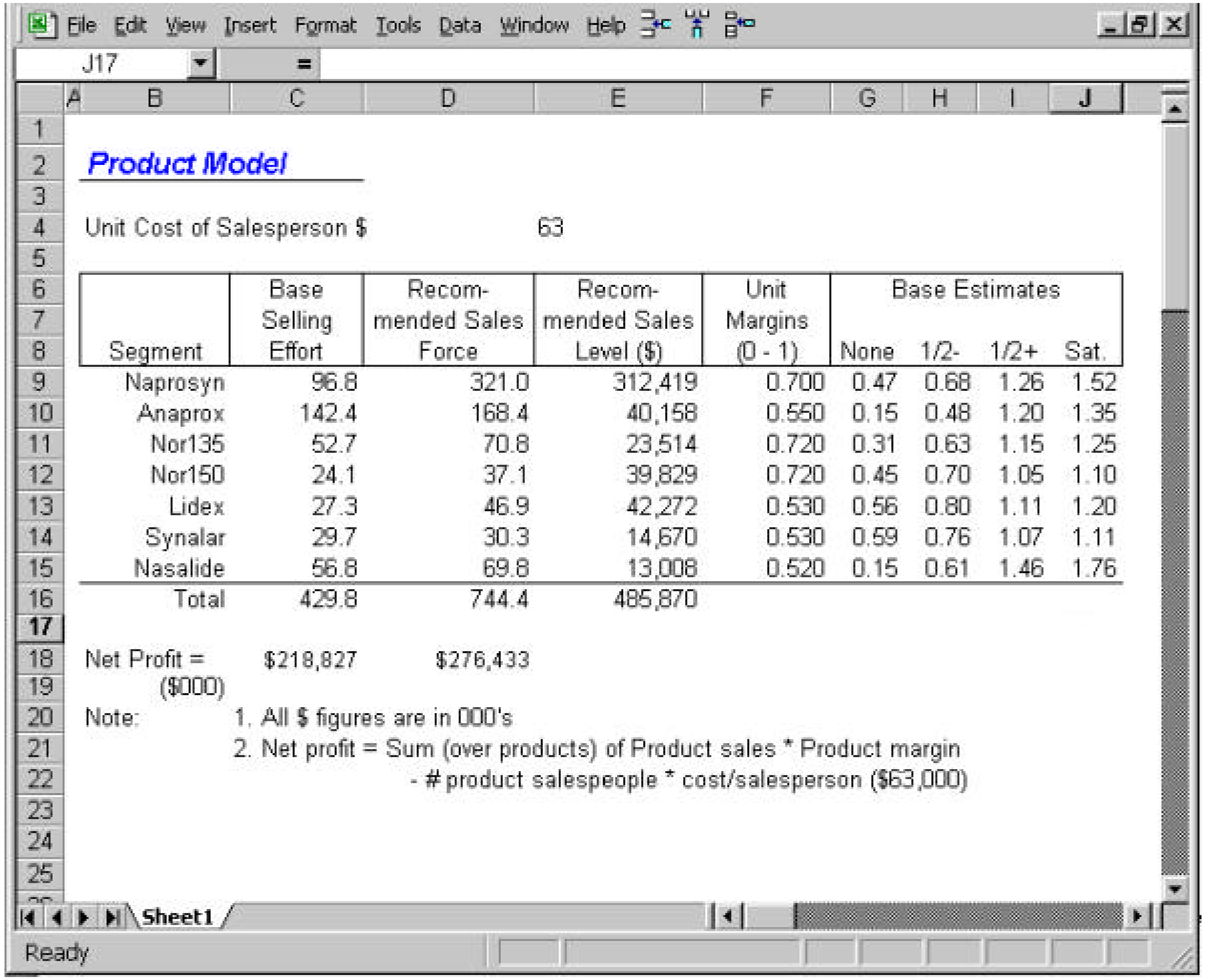
Segment	Base Selling Effort	Base Sales Level ($)	Unit Margins (0 - 1)	Base Response Estimates None	1/2-	1/2+	Sat
Naprosyn	96.8	214,400	0.700	0.47	0.68	1.26	1.52
Anaprox	142.4	36,500	0.550	0.15	0.48	1.20	1.35
Nor135	52.7	21,200	0.720	0.31	0.63	1.15	1.25
Nor150	24.1	37,200	0.720	0.45	0.70	1.05	1.10
Lidex	27.3	38,000	0.530	0.56	0.80	1.11	1.20
Synalar	29.7	14,600	0.530	0.59	0.76	1.07	1.11
Nasalide	56.8	11,200	0.520	0.15	0.61	1.46	1.76
Total	429.8	373,100					

Net Profit = $218,827
($000)

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)

Note: 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.")

Figure 4: Syntex DSS output -- Unconstrained optimization, showing what the model recommends with no restrictions on the amount of selling effort



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)

Figure 5: LISREL model showing overall framework and paths included in the model

Case

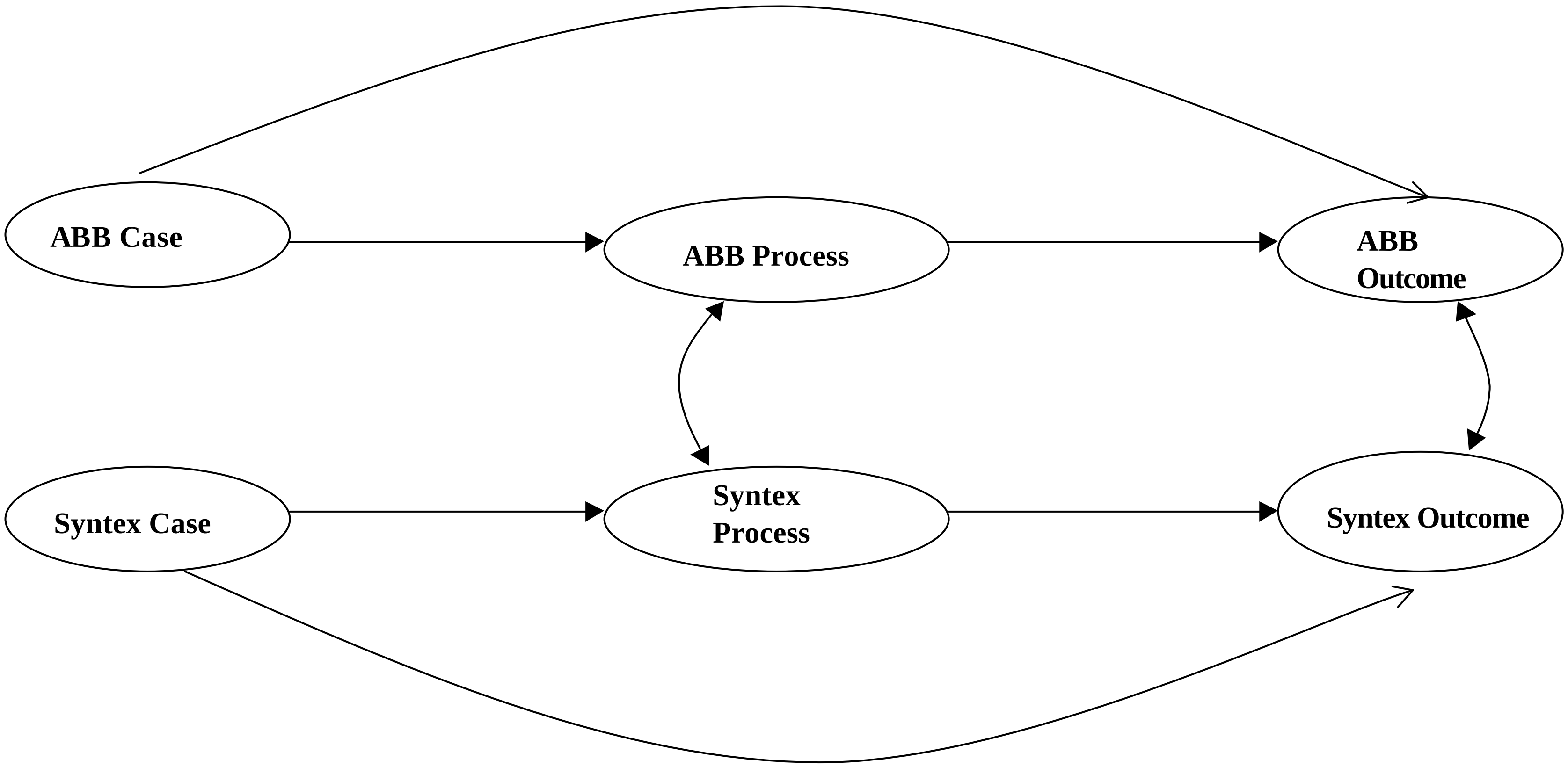
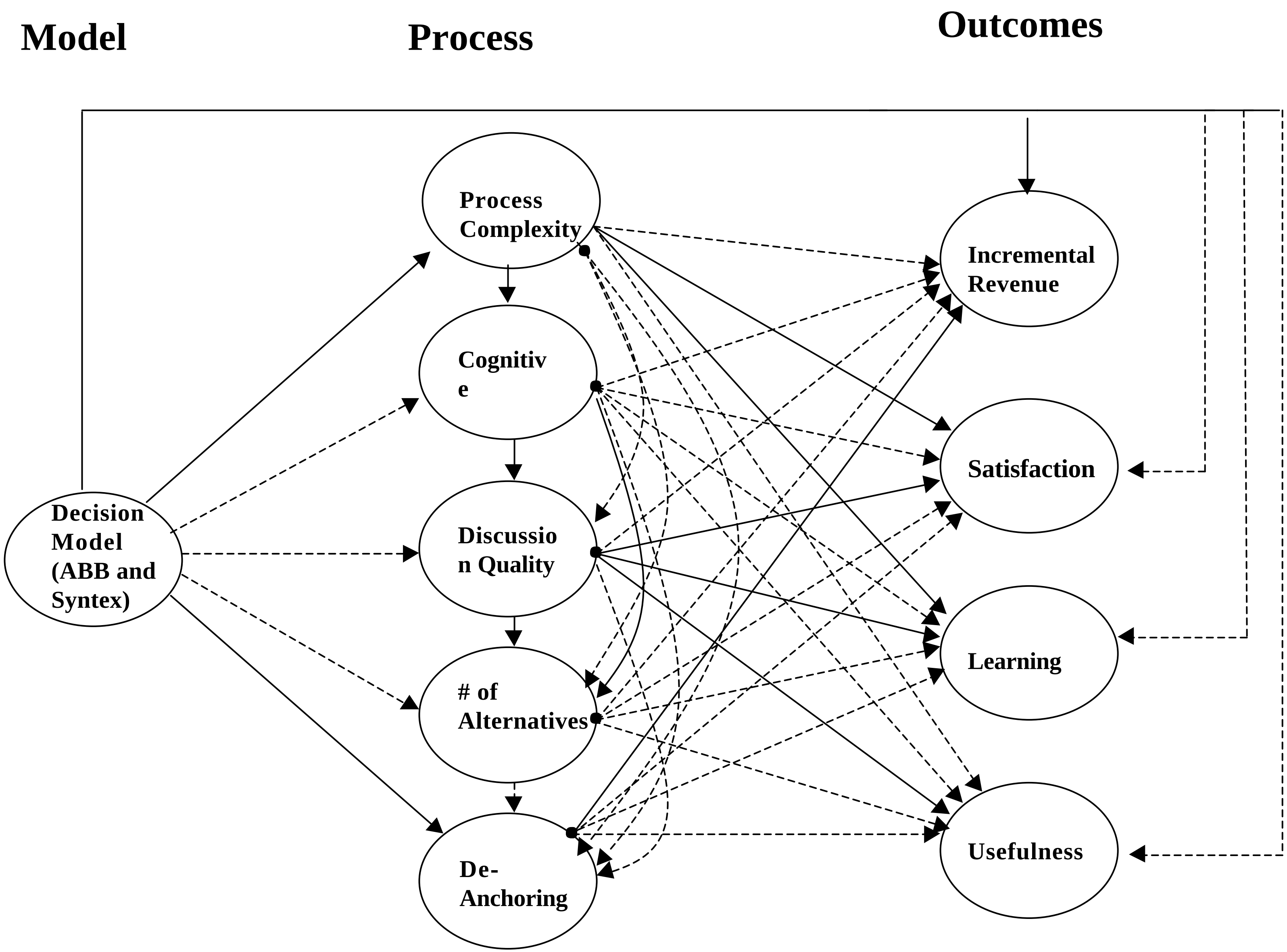


Figure 6: Specific paths included in the LISREL model



A solid line indicates a significant path in our model for ***both*** ABB and Syntex. Note that we used all the paths indicated in this chart for model estimation. See Table 7 for the complete set of significant relationships.

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