

The Effect of Feedback and Learning on Decision-Support System Adoption

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THE EFFECT OF FEEDBACK AND LEARNING ON DSS ADOPTION

Abstract – A well designed decision support system (DSS) of high objective quality may still not be used. There is often a large gap between the objective quality of DSSs and their subjective evaluations, often because DSSs are designed to help decision-makers make better decisions, without necessarily helping them understand why. A large gap between a manager's mental model and the decision model embedded in the DSS may lead to low confidence in the DSS recommendation. We hypothesize that to strengthen DSS effectiveness, the system should not only be of high quality, but must also close any mental model-decision model gap. We identify two design characteristics that lead users to update their mental models, resulting in better DSS evaluations: providing feedback on upside potential as well as providing suggestions for corrective actions. In tandem, they induce managers to update their mental model, a process we call deep learning. We validate our framework in an experimental setting, and also show that feedback of one type only leads to small or negligible levels of deep learning.

Keywords – Decision-support systems; feedback; learning; adoption

1. INTRODUCTION

Firms invest heavily in implementing such IT (Information Technology) systems as CRM (Customer Relationship Management) and ERP (Enterprise Resource Planning), aimed at helping managers make better decisions and become more efficient. But there is continuing uncertainty about the value of such investments in driving productivity improvements, resulting in the view that such IT investments by themselves do not enhance productivity (see, for example, Carr 2004). Only when knowledge workers are able to transform their work through IT do such investments have big payoffs. The challenge then is the design of technology that is not only of good objective quality, but also capable of changing the mental models of knowledge workers.

A similar set of concerns is also noted among researchers studying the value of marketing decision models, such as those incorporated in CRM systems. Several researchers have shown, in field and laboratory settings, that well-designed decision models improve the *objective* quality of decision making (e.g., McIntyre 1982, Lodish et al. 1988, Hoch and Schkade 1996, and Lilien et al. 2004), thus improving performance. However, researchers have also shown that decision makers not only have difficulty in recognizing the value of the decision models they are using, but also do not necessarily feel confident about the decisions they make using those models (e.g., McIntyre 1982, Van Bruggen et al. 1996). Because decision models are usually embedded in decision support systems (DSSs), users do not realize the value of those DSSs either, resulting ultimately in reduced DSS usage and adoption (Davis 1989).

We argue that the value expected from using a DSS is realized only when the DSS is able to bring the mental models of decision-makers closer to the decision model, i.e., update their mental models; the objective quality of the DSS is not sufficient for ensuring that users realize the full value from the decision models embedded in the DSS.

In Figure 1, our 3-Gap Model summarizes our perspective on the DSS evaluation problem. We hypothesize that the size of the gaps between three models of the decision environment – the manager's mental model, the decision model underlying the DSS, and the true model – determines managerial performance and DSS evaluation. In order to have (long lasting) impact, a DSS needs to provide high quality advice or support *and* also be used more often. To provide high quality support,

the gap between the decision model underlying the DSS and the real world model must be small (Gap 2 in Figure 1). A large management science and information systems literature is focused on closing this gap. But for a DSS to be used, we hypothesize that the DSS should contribute towards reducing the gap between the decision model and mental model (Gap 1 in Figure 1) because a smaller gap will make users more comfortable with the results and advice given by the DSS, leading to higher risk-adjusted preferences for the DSS. By definition, if Gap 2 is small, reducing Gap 1 leads to users forming a better understanding of the real world data generating process (reducing Gap 3). Our goal in this paper, then, is to identify DSS design characteristics that lead to a reduction in Gap 1.

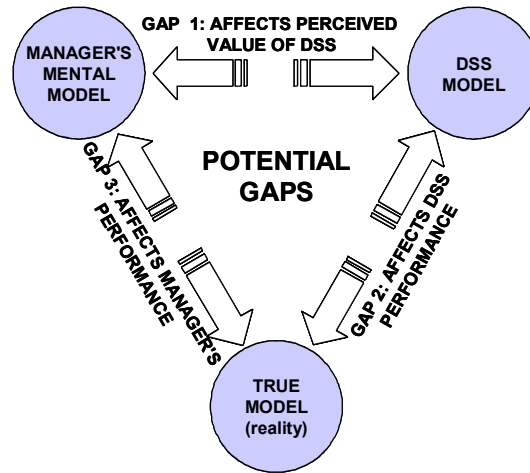


Figure 1. The 3-Gap Model: The Effect of Gaps Between Mental Model, Decision Model, and True Model.

If DSSs must have the ability to change mental models, i.e., reduce Gap 1, the key question then is how to design a DSS that can effect that change. Sprinkle (2000) suggests that individuals must (i) exert effort to change their mental models, but to do so they must know why they should exert effort, i.e., they need to have an incentive, *and* (ii) be given guidance on how they should change their mental model, so that they know where they are going wrong and what action to take to develop a better mental model. We propose and show that a DSS embedded with feedback about upside potential (*what can be achieved*) and corrective actions (*how to achieve it*) provides the answers to the “why” and “how” questions respectively. By doing so, the two characteristics – i.e., feedback on upside potential and corrective actions – together bring the mental model closer to the decision model because these characteristics contribute towards increased (cognitive) effort and increased guidance on deploying that effort. Information about the upside potential, i.e., how much more can be gained, provides users with a salient incentive to update their mental models. Incentives are known to affect motivation and effort, which are necessary for learning in complex decision environments (Locke et al. 1981, Bandura 1986, 1997). Feedback on corrective actions, on the other hand, guides a user on how to improve their mental models of the decision environment (Kluger and Denisi 1996).

Our primary contribution is to show that, by incorporating both these types of feedback (i.e., upside potential and corrective actions), a DSS can help users update their mental models through the complementary effects of the feedback types on the process variables of motivation, effort, and guidance. Consistent with our hypotheses, we show in a laboratory study that the magnitude of change in mental models is dramatically smaller, even null, when only one of these two feedback mechanisms is embedded in the DSS. We also find that the magnitude of change in the users’ mental model significantly affects DSS evaluation. Thus, we find strong support for our argument

that the ability of a DSS to change mental models is an important driver of DSS evaluation, an antecedent of DSS adoption (Davis 1989). We also make a methodological contribution by developing an unobtrusive way to measure a user's mental model, avoiding the biases associated with more obtrusive approaches (Rowe and Cooke 1995).

2. EMPIRICAL STUDY

The solicitation of donations through direct mail for non-profit or charitable organizations provides the context of our study. We constructed a database of 200,000 hypothetical donors, described on four characteristics – their recency of donation, frequency of donation, amount of past donations, and age. These characteristics, described in detail in our initial set of instructions to participants are often used by direct marketing firms in targeting models. We modeled the probability that a particular donor would make a donation as a function of these four characteristics, and designed Gap 2 to be very small by constructing a decision model (embedded in the DSS) that was identical to the true model in terms of weights placed on each of the factors. To obtain a sufficient level of realism, we added a small error component. In the limit, the true model and decision model were identical.

Part 1

We asked each participant to rate 20 donors from the database on how attractive each of the donors was for selection in a marketing campaign, using a 100-point sliding scale, where 0 meant not attractive at all for a solicitation, and 100 most attractive. The 20 donors were described along the four drivers of donation behavior – recency, frequency, donation amount, and age. To obtain the unobtrusive measure of the participant's mental model, we statistically related their donor ratings to the descriptions of the 20 donors and thus inferred the implicit weights being placed by the respondent on each of the four factors.

Once participants submitted their ratings, we estimated a linear regression model to estimate the implicit weights the participant placed on namely, recency, frequency, donation amount and age. We then applied this calibrated mental model to the larger database of 200,000 donors to determine who to solicit and who not to solicit. Note that if participants handed out perfectly accurate scores, mental parameters would be equal to true parameters, and the solicitation strategy would be optimal.

To assist the participants in their decision-making, we provided a DSS to select high expected value customers from a database. We stressed that their ability to identify the best donors in the database was critical for the financial success of the campaign. We varied the feedback provided by the DSS to reflect the four different feedback conditions:

1. **OUTCOME FEEDBACK ONLY:** All participants were informed of the expected performance of the donor rating strategy. For example:
The DSS predicts that a marketing campaign based on your ratings would generate \$61 000 in revenues.
2. **OUTCOME + UPSIDE FEEDBACK:** Participants in this condition were also informed of the maximum financial performance they could have achieved if they had been able to uncover the 'true' attractiveness scores of the 20 donors. For example:
The DSS predicts that it would be possible to generate up to \$99,934 in revenues from this database.
3. **OUTCOME + CORRECTIVE FEEDBACK:** Participants in this condition were given feedback on whether they were placing too much or too little weight on each of the four factors. To

operationalize this feedback, we compared the participants' mental model parameters to the parameters of the decision model. For example:

In developing your ratings for these donors:

- **you are greatly overestimating the importance of frequency.**
 - **you are underestimating the importance of age.**
4. ALL: In this condition, we provided participants with feedback on expected outcome, upside, and corrective actions (conditions 1-3 above).

We had to incorporate different types of feedback in the DSS and have participants use the DSS a number of times. That way we could calibrate participants' mental model at each stage and examine whether the magnitude of change was related to the feedback type embedded in the DSS. In Part 1 of the study, participants were asked to rate the 20 donors, and were given access to a DSS to determine the best possible ratings over a total of ten simulations. In each simulation, the participants rated the 20 donors, submitted those ratings to the DSS simulator, and obtained the DSS's expectation of the performance of the campaign based on the participant's donor rating strategy. In the background, we calibrated the regression relationship between the participant's ratings and the description of the 20 donors on the four factors. The DSS was therefore both a support tool for users to make decisions, and also a research tool to measure users' mental models.

Part 2

We measured deep (as opposed to mechanistic) learning in Part 2 of the study. Per our definition of deep learning, we sought a measure of mental model change that survived a change of conditions. Therefore, in Task 2, we asked participants to rate 20 donors who were different from those in Part 1. To ensure they applied their (updated) mental model of donor behavior to this task, we told them that the 20 new donors were from the same database used in Task 1, so the extent to which each factor impacted donor behavior was the same for these new donors as it was for the donors in Task 1. Because we were only interested in measuring their mental model, we did not provide access to a DSS.

Part 3

The main process variables of interest in this study were motivation, effort, and guidance. After participants completed Tasks 1 and 2, but before they were informed of the financial performance results, we asked them to complete a questionnaire concerning effort provided during the task, motivation to complete the task, and perceived guidance of the DSS.

Analysis and Results

Figure 2 sketches a process model of the effect of DSS design characteristics on deep learning and DSS evaluation, as well as our hypotheses. Notice that dashed lines mean that we hypothesize an *absence* of relationship.

We found strong support that users' evaluations of a DSS would depend on whether the DSS is capable of helping them learn about the decision environment (Hypothesis H1, $p < 0.01$). Next, we tested Hypothesis H2, i.e., whether deep learning is affected by the combination of effort and guidance. The results support H2 ($p < 0.05$). This result shows that the combination of effort and guidance is a significant driver of deep learning. The intercept term is not significant, indicating that deep learning does not occur without effort and guidance. The coefficients for effort and guidance are not significant, indicating that neither of these process variables alone is capable of obtaining deep learning. These results support hypotheses H2.1 and H2.2.

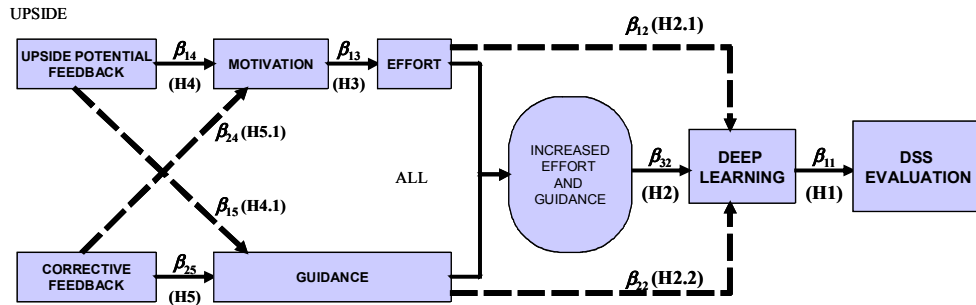


Figure 2. Connecting DSS Design Characteristics, Deep Learning, and DSS Evaluation.

Effort was significantly affected by a participant’s motivation to do better (supporting H3, $p < 0.01$), while a participant’s motivation to do better was significantly increased by the presence of upside potential feedback (supporting H4; $p < 0.01$). As expected, motivation to do better was not affected by corrective feedback (supporting H4.1, *ns*). Guidance, the other component of guided effort, significantly increased with the presence of corrective feedback (supporting H5, $p < 0.01$). Surprisingly, guidance also increased significantly when participants were provided upside potential feedback (does not support H5.1, $p < 0.05$). We find that deep learning is significantly different from zero in the ALL condition ($p < 0.01$), not surprising given the high level of guided effort in this condition.

Deep learning was not found to be significantly different from zero in either the OUTCOME or OUTCOME + CORRECTIVE condition. There is weak evidence that deep learning in the OUTCOME + UPSIDE condition is significantly different from zero ($p < 0.10$). This result is consistent with the significance of the effect of upside potential feedback both on effort and guidance, the two conditions required for deep learning to occur.

3. DISCUSSION AND CONTRIBUTIONS

For DSSs to be adopted and used, it is not sufficient that they be capable of generating high quality decisions (i.e., low Gap 2 in Figure 1); they must also be able to change users' mental models, aligning them with that of the DSS (i.e., have low Gap 1 in Figure 1). To bring about such changes in the mental model, DSSs should be designed to facilitate users' deep learning, driving users to internalize the logic behind system recommendations.

Our results show that deep learning is crucial for users to form a favorable DSS evaluation, a pre-cursor to adoption. Specifically, our study shows that a DSS with upside potential feedback can motivate users to perform better, resulting in greater user effort. However, increased effort alone is not sufficient to generate deep learning; the DSS must also provide clear guidance about how and why a modification of a decision process leads to a superior outcome.

In sum, our results suggest that DSS feedback not only influences decision outcomes directly (performance), but also influences the underlying learning process of the users, which in turn, helps them internalize the relationship between decisions and outcomes. Most prior research has only examined decision outcomes, and not the underlying processes by which DSS influences outcomes, revealing only part of the story. Our study helps enrich the story by providing new insights about why objectively superior DSSs are often not evaluated more positively by users.

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APPENDIX

Project HOPE

Description of 20 donors

Id	Recency <small>(what's this?)</small>	Frequency <small>(what's this?)</small>	Amount <small>(what's this?)</small>	Age <small>(what's this?)</small>
1	20	3	\$ 11	74
2	6	1	\$ 98	30
3	12	4	\$ 81	65
4	13	6	\$ 75	32
5	19	2	\$ 100	26
6	10	1	\$ 41	54
7	8	6	\$ 87	25
8	15	9	\$ 29	35
9	20	1	\$ 48	68
10	1	2	\$ 35	42
11	9	3	\$ 19	39
12	5	5	\$ 62	72
13	18	9	\$ 12	46
14	3	10	\$ 55	50
15	4	8	\$ 99	70
16	20	10	\$ 91	58
17	17	10	\$ 69	75
18	2	7	\$ 23	75
19	16	10	\$ 95	61
20	1	8	\$ 15	28

Where you will enter your ratings

Least attractive donors	Ratings	Most attractive donors
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50
		50

Submit ?

Screen capture of the decision-support system used in the study (input screen)