Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2010 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

2010

Designing Effective Decision Support Using Decisional Guidance

Alison Parkes
The University of Melbourne, aparkes@unimelb.edu.au

DESIGNING EFFECTIVE DECISION SUPPORT USING DECISIONAL GUIDANCE.

Alison Parkes, Accounting & Business Information Systems, The University of Melbourne, Victoria, Australia, aparkes@unimelb.edu.au

Abstract

This study explores the decision outcomes achieved by 122 subjects using a DSS for an insolvency decision making task. Decision quality improvements occur as a result of collaboration between the decision maker and the DSS at two crucial points in the decision making process. Firstly when the decision maker initially interacts with the DSS to generate a recommendation, and secondly when the decision maker decides whether to incorporate that recommendation into their decision. Good technology design will assist a decision maker to generate a high quality recommendation; however the ensuing acceptance or otherwise of the recommendation is what ultimately affects the decision outcome. The study encompasses exploration of DSS use, and how decision outcomes are subsequently impacted. The results show that providing decisional guidance, in particular suggestive guidance, helped novice decision makers produce higher quality recommendations; and that adoption of those recommendations improved decision quality. The results are consistent with the theoretical premise that a key design issue is providing appropriate guidance to fit the task and individual, rather than simply guidance per se. The results show decision performance is a function of both how the technology is designed and used; and whether the user incorporates the recommendation received into their final decision. DSS use is a necessary, but not sufficient, precursor to improved decision outcomes.

Keywords: decisional guidance, decision support system, use, performance outcomes

1. INTRODUCTION

Decision support systems (DSS) are purposeful artifacts, generally created with the intention of improving some aspect of decision making. Desirable improvements to decision quality occur as a result of collaboration between the decision maker and the DSS; for a positive change in decision quality to occur two conditions must be satisfied. Firstly the decision maker must interact with the DSS so as to produce a high-quality recommendation or output; and secondly that DSS recommendation must be incorporated into the final decision.

Decision outcomes are triggered by interactions between the task, the individual, and the technology itself (DeSanctis and Poole 1994; Markus and Silver 2008) and the degree of fit or alignment between these factors (Davern 2007; Goodhue 1998; Goodhue and Thompson 1995; Te'eni 2005). Goodhue and Thompson (1995) propose that task-technology fit must be established before use of the technology can impact individual performance. The degree of fit between the individual, task and technology is primarily determined by the design of that technology. Decision support technology which is poorly designed, and as a consequence a bad fit to the task or user, is likely to be ignored or overridden (Davis and Kotteman 1994; Davis and Kotteman 1995; Kachelmeier and Messier 1990). As DSS design motivates how and how much a decision maker interacts with the DSS, DSS design should be deliberate and purposeful. The underpinning theme of this research is that good technology design will assist the decision maker to generate an expert like recommendation, then the acceptance or otherwise of this recommendation will affect the decision outcome.

The task context for the study is insolvency, where a decision whether to liquidate a distressed business or to trade-out of its present difficulties is made for any company that enters into administration. The research uses a purpose-built DSS, Insolve-DG, to support novice decision makers. Decision support is intended to bridge any gap between the degree of task expertise currently possessed by the decision maker, and the degree of task expertise required to complete the decision task well; consequently the subjects selected for the research have little or no task expertise. When a novice decision maker draws on expertise supplied via a DSS it makes the novice more capable of performing the task in an expert like manner (Blattberg and Hoch 1990; Connolly and Thorn 1987); a good decision outcome for a novice is an outcome which closely resembles that which an expert would have achieved for the same task. This research explores whether and how desirable, expert like, outcomes are affected by the DSS design.

The structure of the remainder of the paper is as follows: the following section describes the theoretical basis of the research and presents the hypotheses derived. Methods employed and results obtained are then presented. In the final section of the paper the results obtained, conclusions reached and their related implications are discussed.

2. THEORY AND HYPOTHESES

Adaptive structuration theory (DeSanctis and Poole 1994) proposes that technology effects emerge from user interactions with the technology, therefore the design of that technology must be highly significant. Design choices should be made explicitly and consciously; failure to design overtly can lead to unintentional emergent effects occurring. Good design helps users understand and access system features appropriately, with users becoming more able to obtain value from the use of the technology. The ability to design so as to motivate users to appropriate the technology faithfully is particularly important for DSSs, where use of the technology to complete a specific task is often optional. Research questions relating to DSS design generally have been widely studied (see for example Arnold et al. 2006; Fildes et al. 2006; Kamis et al. 2008; Moreau 2006); this research focuses on the specific issues relating to the design of decisional guidance features (Silver 1988; Silver 1990; Silver 1991).

Silver (1991) suggests that all systems guide in some manner, whether intentional or otherwise, and that guidance choices can change system users' behaviour, and alter the outcomes of systems use. Decisions relating to guidance ideally should be made explicitly and deliberately "…deciding whether or not to provide guidance is essentially a choice between accepting the effects of inadvertent guidance and opting to guide deliberately. Indeed, trying to offset inadvertent guidance effects may be the reason for choosing to guide deliberately" (Silver 1991:111). Decisional guidance is how a system informs or influences the system users (Silver 1990); it is a tool that designers can employ to improve technology design, and increase the incidence of faithful appropriation of the technology. Examples of decisional guidance include offering explanation and help facilities, and providing navigational support using menus or hyperlinks. Empirical studies find support for the idea that decisional guidance is an important explanatory variable for system use and user behaviour (Jiang and Klein 2000; Limayem and Desanctis 2000; Mahoney et al. 2003; Montazemi et al. 1996; Parikh et al. 2001; Silver 1991; Wilson and Zigurs 1999). Several studies identified positive performance effects as a result of offering decisional guidance (Montazemi et al. 1996; Parikh et al. 2001). Wilson and Zigurs (1999) noted that users welcome decisional guidance as long as it does not restrict their use of the system.

Obviously decisional guidance is intended to be helpful. Indeed, from an informational perspective guidance should be viewed as useful, since users are provided with more information. However this normative expectation may not hold descriptively in practice (Bell et al. 1988). For example, the additional information provided may result in information overload or confusion for the user (Connolly and Wholey 1988). Prior research reveals that when users underestimate the usefulness of a DSS (Davis and Kotteman 1995) they may elect not to use the system.

Decisional guidance provides additional material for the decision maker to consider; allowing the decision maker to more readily access expert like opinions and information designed to fit with a specific task and user. The thoughtful provision of decisional guidance should make it more likely that a novice decision maker using the DSS will generate a recommendation resembling an expert opinion. Contrasting the provision of deliberate decisional guidance to the laissez fare approach of providing no guidance, a thoughtfully designed decisional guidance intervention should act to improve the quality of the recommendation generated by a novice user of a DSS, leading to the first hypothesis:

H1: Novice decision makers using a DSS containing deliberate decisional guidance will generate recommendations more closely resembling an expert opinion.

In terms of the purpose of decisional guidance, Silver (1990) distinguishes between two broad types of decisional guidance. Informative Guidance involves enlightening a decision-maker by providing provides additional material (e.g., definitions of terms) that is pertinent to the decision. Suggestive Guidance involves swaying a decision-maker by providing a recommendation on how to proceed during the interaction with the DSS (i.e., guidance on interim judgments and component decisions, not just on a final choice). A DSS may contain both forms of decisional guidance, and either, or both, may be offered at any judgment point (Silver 1990). Informative guidance provides additional information cues, however suggestive guidance provides an opportunity for the decision-maker to either create or extend their knowledge of patterns within the problem domain; this research explores how these varying forms of decisional guidance fit a given decision task.

Considering the design of decisional guidance further and returning to theories of fit; it seems clear that we should expect that differing forms of decisional guidance would produce differing performance effects. Montazemi (1996) found some support for the idea that providing informative guidance will produce better decision outcomes generally, however a later study by Parikh (2001) found that suggestive guidance produced better decision quality and user satisfaction, in less time. Based on these empirical results, it seems that both forms of guidance impact on the decision maker, and therefore on the recommendations they generate while using the DSS.

Novice decision makers are characterised by a lack of task expertise. Expertise is partially related to the ability to develop knowledge of archetypal situations, and prepare a store of suitable actions to take for those situations (Chase and Simon 1973; Newell 1990), expertise develops through the creation of processes or patterns for particular tasks or activities (Salthouse 1991). In the case of novice decision-makers, who have not yet developed this pattern expertise, an important basic issue is that of processing power. Novice decision-makers need to be able to deal with large numbers of information cues without being able to resort to the heuristics or patterns that true experts have developed (Bereiter and Scardamalia 1993). By its nature, informative guidance provides additional information cues, which would be useful in provoking expert like behaviour only where there is spare processing capacity available allowing the decision maker to incorporate additional information cues (Miller 1956); informative guidance is therefore potentially a suboptimal fit to novice decision makers. In contrast suggestive guidance, which provides an interim recommendation as to how to proceed, and substitutes for the missing expert pattern knowledge, would seem to act to improve the degree of fit to novice users. The ability to undertake a decision task utilising the expert like patterns provided by suggestive guidance will enable a novice decision maker to generate a more expert like recommendation from the DSS, leading to the second hypothesis:

H2: Novice decision makers using a DSS containing suggestive guidance will generate recommendations more closely resembling an expert opinion.

The ability to interact with a DSS and receive an expert like recommendation is a necessary, but not sufficient, precursor to improvements in decision quality. In order to have a positive effect on the decision outcome the decision maker must accept the recommendation provided, and incorporate it into their decision. Based on the hypothesised ability of decisional guidance to improve the quality of recommendations generated by novices, this section of the study extends beyond this initial exploration of DSS use to consider how performance outcomes are subsequently impacted. In line with prior work by Devaraj and Kohli (2003), this research explores the impact of use of the DSS in terms of individual performance outcomes, proposing that a high quality recommendation received as a result of use of a DSS will positively impact the decision quality achieved. Assuming that novice decision makers are by themselves not consistently capable of independently making an expert like decision leads us to two possible consequences when an expert recommendation is received. The novice decision maker could reject the recommendation, in which case use of the DSS would have no effect on the decision quality; alternatively they could accept the recommendation, in which case use of the DSS would improve decision quality. Given the knowledge gap between the complex task presented and the existing novice level of knowledge of subject it is anticipated that a reliance effect (Barr and Sharda 1997; Brown and Jones 1998; Kaplan et al. 2001) will develop, leading to acceptance of the DSS recommendation and improved quality of the decision outcome.

H3: Provision of an expert like DSS recommendation will result in novice decision outcomes more closely resembling an expert opinion.

3. METHOD

The hypotheses were tested in an experimental setting; subjects were randomly assigned to one of three versions of the DSS. 135 subjects successfully completed the experiment in 12 experimental sessions conducted over 3 months; all the experimental sessions used identical scripts and procedures. Subjects were recruited directly by the researcher. Descriptive statistics revealed that 13 of the subjects reported more than 5 years task experience; data relating to these more expert subjects was removed from the sample. Subjects were asked to read the case study materials and record an initial (unaided) opinion for the case then, after using the supplied DSS, record a second (aided) case opinion. Descriptive statistics contained in table 1 show that the average subject was 24 years old, had just over 3 years of work experience and one year of insolvency related work experience.

	Subjects			
	Mean	**Minimum**	**Maximum**	**Std Deviation**
Age	24.4	18	49	4.088
Work Experience (Years)	1.37	0	30	4.187
Insolvency Experience (Years)	1.08	0	5	1.568

Table 1: Descriptive statistics - subjects

The experimental task was a judgment task requiring subjects to make an insolvency related trade on / liquidate decision for a business entering administration, initially unaided and subsequently after using the DSS. The experimental case study narrative was developed and written by the researcher based on appendix materials collected as part of an unrelated project into insolvency decision making (Leech et al. 2003). Case narrative development included identifying and inserting information cues; additional material was devised by the researcher to provide relevant information cues not considered in the existing appendix materials. Cue coverage was such that there was case study data available to provide a response to any question posed by the DSS. The case study complexity was geared highly enough to provide a challenging environment for novice practitioners.

The decision model in Insolve-DG was validated by three expert insolvency practitioners who indicated that the model accorded with their ‘real world’ view of the insolvency decision making process. These expert practitioners were also asked for an opinion on the case study; all three experts offered the opinion that they would recommend liquidation of this business. These three concurring expert opinions form the basis of the ‘expert like’ outcome aspired to be achieved by the novice subjects.

Insolve-DG is a DSS purpose built for a program of behavioural research about the effects of decisional guidance on decision making behaviour. The purpose of Insolve-DG is to provide a recommendation for action after posing a series of questions about relevant insolvency factors. Subjects answer these questions by reference to the case study materials provided. Three versions of the purpose built DSS (Insolve-DG) were created based on the forms of decisional guidance required (informative guidance, suggestive guidance, no guidance); in all versions the underlying decision model was identical. Insolve-DG incorporates an underlying decision model and materials gathered in an extensive knowledge acquisition effort that led to the original INSOLVE system (Arnold et al. 2004a; Arnold et al. 2004b; Collier et al. 1999; Leech et al. 1999), but in all other respects it is an independent and distinct artifact. The relationships between these two artifacts are explored more fully in Davern and Parkes (2008). At the completion of each laboratory session subjects were asked whether they would use this DSS if it was available in their workplace. Over 95% of subjects completed this question; close to 90% of the subjects indicated that they would use the aid if they worked in insolvency and it was available; indicating that the DSS was seen as credible by subjects.

Suggestive guidance was operationalised in Insolve-DG by leveraging the existing hierarchical structure of the decision model. Specifically, where multiple underlying factors contributed to an interim judgment within the decision model, the opportunity existed to both ask users directly for the interim judgment and provide suggestive guidance as to that interim judgment. After extensive modelling exercises, an additive model was found to be the most effective way of generating the suggestive guidance. Figure 1 shows the relevant underlying factors and then the resulting suggestive guidance.

Example underlying factors: Question 3. Will the practitioner get paid?

3.1 Will there be sufficient funds to pay the practitioners fees and ongoing expenses?

3.2 Is a challenge to the practitioner’s priority to receive payment of their fees and expenses unlikely?

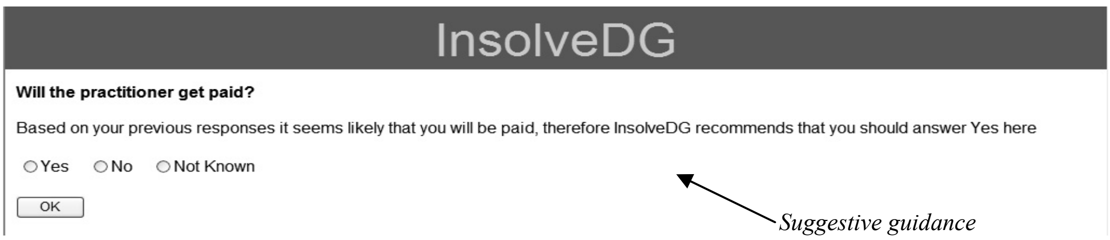

Figure 1: Suggestive guidance operationalisation

Informative guidance in the form of definitional text was also embedded into appropriate questions in Insolve-DG as shown in figure 2.

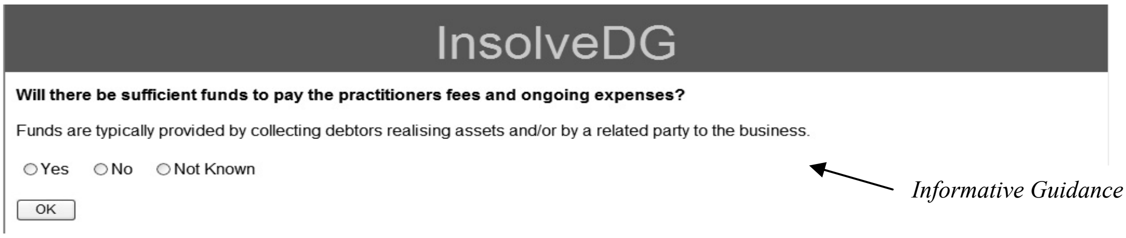

Figure 2: Informative guidance operationalisation

3.1. Operationalising Recommendation

Hypothesis 1 and 2 examine the impact of decisional guidance on the recommendation generated by use of the DSS, arguing that decisional guidance overall acts to improve the quality of the recommendation, and that suggestive guidance in particular is the form of guidance which best fits the task and user. The recommendation produced by the aid is to either trade the business on, or liquidate the business immediately. Three expert opinions were solicited for the experimental case study; all three experts advised that they would recommend immediate liquidation of this business. This liquidate recommendation was therefore adopted as the expert like opinion for the case study.

The user interface for Insolve-DG contains data logging functionality to monitor and record user keystrokes. In addition to user keystrokes the data logs records which recommendation was delivered to each user. Data relating to the recommendations delivered was extracted from the session logs and coded, using a value of 0 where the recommendation differed from the expert opinion (i.e. the DSS recommended trade on) and 1 where the recommendation aligned with the expert opinion (i.e. the DSS recommended liquidation). Table 2 contains descriptive statistics relating to the recommendations generated.

3.2. Operationalising Decision outcome

Decision outcome was recorded immediately after the subject worked through the case study unaided, and then again after they had used the DSS. The question posed was as follows; subjects were requested to tick the applicable box

> *"What decision would you make: liquidate (sell the assets and close the business) or trade on (continue the business, possibly in some other form)?"*

Liquidate ☐ *or* ***Trade on*** ☐.

The decision outcome data was coded using a value of 0 where the decision differed from the expert opinion (i.e. the subject decided to trade on) and 1 where the decision aligned with the expert opinion (i.e. the subject decided to liquidate). Both decisions were recorded and coded in the same way; the decision taken prior to use of the DSS is referred to as the "Unaided" decision, the decision made after using the DSS is referred to as the "Aided" decision. Table 2 contains descriptive statistics relating to these decision outcomes.

3.3. Control variables

Although all subjects are novices in terms of insolvency experience the descriptive statistics contained in table 1 indicate some variability in terms of their self reported exposure to insolvency tasks. In order to discount the possibility of a systematic expertise effect a control variable for task experience was included in all analyses. Task experience was solicited using a question asking subjects how many years of insolvency related work experience they had.

Both the recommendation generated by the DSS and the decision outcome obtained after use of the DSS are potentially prejudiced by the expectations of the decision maker, based on their initial unaided decision. Given the need to isolate the effects of decisional guidance design, and the DSS recommendation, it is crucial to extract out whether and how subjects' decisions were impacted by actual use of the DSS, in contrast to their innate belief as to the 'correct' outcome for the case. The subjects' unaided decision was recorded prior to use of the DSS and establishes this innate belief. A control variable capturing this unaided decision outcome was included in all analyses. The unaided decision outcome was captured and coded as described above in relation to the aided decision outcome. Descriptive statistics relating to the unaided decisions are contained in table 2. Exploratory analysis of these recommendation and decision outcomes using ANOVA revealed that while decisional guidance had no significant effect on either the unaided or aided decision, the form of decisional guidance provided did significantly affect the recommendation generated (p.<.000).

	Overall		**Suggestive Guidance**		**Informative Guidance**		**No Guidance**	
	Freq.	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
Unaided Decision								
Liquidate (expert like)	71	58.2	31	72.1	22	53.7	18	47.4
Trade on	51	41.8	12	27.9	19	46.3	20	52.6
Total	*122*	*100.0*	*43*	*100.0*	*41*	*100.0*	*38*	*100.0*
Recommendation								
Liquidate (expert like)	92	75.4	41	95.3	29	70.7	22	57.9
Trade on	30	24.6	2	4.7	12	29.3	16	42.1
Total	*122*	*100.0*	*43*	*100.0*	*41*	*100.0*	*38*	*100.0*
Aided Decision								
Liquidate (expert like)	81	66.4	34	79.1	25	61.0	22	57.9
Trade on	41	33.6	9	20.9	16	39.0	16	42.1
Total	*122*	*100.0*	*43*	*100.0*	*41*	*100.0*	*38*	*100.0*

Table 2 – Descriptive statistics - recommendations and decisions

3.4. Model estimations

As the dependent variables of interest are dichotomous all hypotheses are tested using logistic regression models. Model 1 tests the effects of decisional guidance on the recommendation generated by the user of the DSS. Model 2 tests the differential effects of suggestive versus informative guidance on the recommendation generated by the user of the DSS. Model 3 tests the effect of the recommendation received on the decision outcome. All 3 models contain control variables to allow for the unaided decision made by the subject, and the task experience of the subject. Model 3 also contains control variables to allow for the effect of the varying forms of decisional guidance.

$$\text{Recommendation} = \beta_0 + \beta_1 G\_NG + \beta_2 EXP + \beta_3 UD + \varepsilon \qquad (1)$$

$$\text{Recommendation} = \beta_0 + \beta_1 SG + \beta_2 IG + \beta_3 EXP + \beta_4 UD + \varepsilon \qquad (2)$$

$$\text{Decision Outcome} = \beta_0 + \beta_1 REC + \beta_2 IG + \beta_3 SG + \beta_4 EXP + \beta_5 UD + \varepsilon \qquad (3)$$

where
G-NG Is a dummy variable for decisional guidance (1=decisional guidance, 0=otherwise)

SG Is a dummy variable for suggestive guidance (1=suggestive guidance, 0=otherwise)

IG Is a dummy variable for informative guidance (1=informative guidance, 0=otherwise)

REC Is a dummy variable for the recommendation received (1=expert like, 0=otherwise)

EXP Is the control variable for task experience

UD Is the control variable for the unaided decision dummy coded as 1=expert like, 0=otherwise

Model 1 directly compares the effects of the guided vs. non guided DSS. The specification of Model 1 has no guidance as a base case, as the model collapses to the following when G_NG=0:

$$\text{Recommendation} = \beta_0 + \beta_2 EXP + \beta_3 UD + \varepsilon \quad (4)$$

For H1 to be supported, β_1 in Model 1 must be significant to evidence an effect for decisional guidance; this would indicate a significant difference from the no decisional guidance base case.

Model 2 compares the effects of the differing forms of decisional guidance. The specification of Model 2 also has no decisional guidance as a base case as the model collapses into the following when IG=0 and SG=0:

$$\text{Recommendation} = \beta_0 + \beta_3 EXP + \beta_4 UD + \varepsilon \quad (5)$$

For H2 to be supported, β_1 in Model 2 must be significant to evidence an effect for suggestive guidance; indicating a significant difference from the no decisional guidance base case.

Model 3 directly compares the effects of the recommendation received on the decision outcome recorded. The specification of Model 3 has the non expert like recommendation as a base case, as the model collapses to the following when REC=0:

$$\text{Decision Outcome} = \beta_0 + \beta_2 IG + \beta_3 SG + \beta_4 EXP + \beta_5 UD + \varepsilon \quad (6)$$

For H3 to be supported, β_1 in Model 3 must be significant to evidence an effect for the expert like recommendation received; this would indicate a significant difference from the non expert like recommendation base case.

4. RESULTS

Hypothesis 1, which examines the effect of decisional guidance on the recommendation generated, was tested using logistic regression. The results obtained are shown in table 3 below. Logistic regression was used as the dependent variable of interest to this analysis (Recommendation) is a categorical (binary) variable. Logistic regression supports testing of models predicting a categorical outcome (Tabachnick and Fidell 2001).

Logistic regression - Recommendation Probabilities (n=122)						
Model 1	**ß**	**Std. Error**	**Wald**	**df**	**Sig**	**Exp ß**
β1 G_NG	***1.211***	***.489***	***6.133***	***1***	***.013***	***3.358***
β2 EXP	-.210	.148	2.007	1	.157	.811
β3 UD	2.003	.509	15.483	1	.000	7.411
Model statistics						
Chi-square 28.405. Nagelkerke R^2 =.309. Cox and Snell R^2 = .208						

Table 3: Results – Hypothesis 1

Model 1 explains between 21 & 31% of the variation in the recommendation received. Results related to the goodness of fit of the model indicate that the model performs well, returning a chi-square value of 28.41 with 3 degrees of freedom ($p<.000$). As β_1 in Model 1 is significant Hypothesis 1 is supported ($p=.013$). Providing decisional guidance is shown to be a significant predictor of producing an expert like recommendation. A subject using a DSS containing decisional guidance is more likely to generate an expert like recommendation than a subject not provided with decisional guidance. Providing decisional guidance increased the probability of generating an expert like recommendation by a factor of 3.4.

Hypothesis 2, which examines the effect of various forms of decisional guidance on the recommendation generated, was also tested using logistic regression. The results contained in table 4 were obtained:

Logistic regression - Recommendation Probabilities (n=122)						
Model 2	**ß**	**Std. Error**	**Wald**	**df**	**Sig**	**Exp ß**
β1 SG	***2.545***	***.833***	***9.322***	***1***	***.002***	***12.740***
β2 IG	.570	.527	1.167	1	.280	1.768
β3 EXP	-.208	.151	1.906	1	.167	.812
β4 UD	1.917	.522	13.472	1	.000	6.798
Model statistics Chi-square 35.739. Nagelkerke R^2 =.378. Cox and Snell R^2 = .254						

Table 4: Results – Hypothesis 2

Model 2 explains between 25% & 38% of the variation in the recommendation received. Results related to the goodness of fit of the model indicate that the model performs well, returning a chi-square value of 28.41 with 4 degrees of freedom (p<.000). As β_1 in Model 2 is significant Hypothesis 2 is supported (p=.002). Providing suggestive decisional guidance is shown to be a significant predictor of producing an expert like recommendation. A subject using a DSS containing suggestive decisional guidance is more likely to generate an expert like recommendation than a subject provided with no decisional guidance. Providing suggestive guidance increased the probability of generating an expert like recommendation by a factor of 12.7. In terms of ability to generate an expert like recommendation subjects provided with informative guidance were not significantly different from subjects provided with no guidance,

Hypothesis 3, which examines the effect of the recommendation received on the decision outcome, was also tested using logistic regression as the dependent variable of interest to this analysis (decision outcome) is also a categorical (binary) variable. The results contained in table 5 were obtained:

Logistic regression - Decision Outcome (n=122)						
Model 3	**ß**	**Std. Error**	**Wald**	**df**	**Sig**	**Exp ß**
β1 REC	***3.703***	***.792***	***21.883***	***1***	***.000***	***40.564***
β2 SG	-.853	.767	1.238	1	.266	.426
β3 IG	-.710	.749	.897	1	.344	.492
β4 EXP	.239	.209	1.310	1	.252	1.270
β5 UD	2.447	.592	17.107	1	.000	11.554
Model statistics Chi-square 73.125. Nagelkerke R^2 =.625. Cox and Snell R^2 = .451						

Table 5: Results – Hypothesis 3

Model 3 explains between 45% & 63% of the variation in the decision outcome. Results related to the goodness of fit of the model indicate that the model performs well, returning a chi-square value of 73.125 with 5 degrees of freedom (p<.000). As β_1 in Model 3 is significant Hypothesis 3 is supported (p<.000). Receiving an expert like recommendation is shown to be a significant predictor of making an expert like decision. Subjects receiving an expert like recommendation are more likely to make an expert like decision than subjects receiving a recommendation differing from an expert opinion. Receiving an expert like recommendation increased the probability of making an expert like decision by a factor of 40.5.

5. CONCLUSION AND DISCUSSION

Providing decisional guidance helps novice decision makers produce an expert like recommendation from a DSS; receiving an expert like recommendation from a DSS improves the quality of the decision outcome. When comparing the two forms of deliberate decision guidance (informative; suggestive) the findings show that the performance of novice decision makers, in terms of producing an expert like recommendation from the DSS, is greatly improved by the introduction of suggestive guidance. The results are consistent with the theoretical premise that the key issue is about providing appropriate guidance to fit the task and individual, rather than simply guidance per se.

That suggestive guidance enhances novices' ability to generate expert like recommendations is consistent with theories of expert pattern knowledge. The results show that the ability of novices to generate expert like recommendations improves in response to the pattern knowledge provided by suggestive guidance. The inability of novices to access and leverage informative guidance is consistent with the lack of processing power theorised earlier, in relation to novices and their ability to incorporate additional cue based information.

The findings show that the recommendation received by the decision maker while using the DSS directly and strongly affects the ultimate decision made. Appropriate DSS design results in improved performance outcomes, albeit indirectly. Good design produces good recommendations, good recommendations improve performance outcomes. Interestingly, descriptive frequency statistics indicate that if all subjects had just blindly followed the recommendation received, more of these subjects would have made an expert like decision. In line with prior research findings, even though the subjects possessed nil or very little task knowledge some still ignored the recommendation offered by the DSS.

Results for all three models indicate that a strong influence is exerted by the subject's initial unaided decision; both in terms of the recommendation generated and the final decision outcome. This result is not surprising, the subjects' initial reading and assessment of the case study will tend to colour both the way they answer the questions posed by the DSS, and their final decision. What is interesting is that the effects of the design of the decisional guidance, and the recommendation received, are observable even after allowing for this influential intrinsic position.

The results are consistent with theories of use and task-technology fit; improved performance outcomes are a result of appropriate combinations of individual, task and technology factors. A comprehensive understanding of effective decision support requires consideration of technology design, as well as the fit between the individual and the task.

5.1 Implications

The research seeks to understand how decisional guidance design affects use of a DSS; additionally it examines the effects of DSS use, in terms of impact on decision outcomes. The research shows that performance outcomes for novice users of a DSS vary based on whether and how they accept the support offered by the DSS. Decisional guidance design does matter; the thoughtful design of decisional guidance is integral to improving decision outcomes. What are required are designs that appropriately consider user as well as task characteristics. Suggestive guidance encodes the patterns of knowledge that make experts successful; the results suggest that most novice users are both willing and able to leverage this pattern knowledge if offered.

The practical implications drawn from this study relate to opportunities to improve DSS design. Organisations spend time and money creating DSS with the intention of improving decision outcomes; however no effect can occur unless decision-making performance improves. We can return value from the DSS investment to the organisation by improving decision quality and reducing organisational risk. The results show decision performance is a function of both how the technology is designed and used; and whether the user accepts and incorporates recommendation received from the DSS. DSS use is a necessary but not sufficient condition to improve decision performance.

5.2 Limitations

This study has several limitations. Data was collected in a laboratory based experimental setting, which maximises environmental control but introduces some limitations in terms of the richness of the experience for subjects. Because of this behaviour of subjects in a real world setting may differ. The experimental session and data recorded identify only short term effects; a longitudinal study may result in different outcomes. Given the specific problem domain generalisability of the results may be limited, although these results will generalise to any judgment task which contains similar characteristics to insolvency decision-making. There is also a possibility that the results obtained may relate only to the specific task and software artefacts in use.

References

Arnold, V., Clark, N., Collier, P.A., Leech, S.A., and Sutton, S.G. "Explanation Provision and Use in an Intelligent Decision Aid," *International Journal of Intelligent Systems in Accounting, Finance & Management* (12:1) 2004a, pp 5 - 28.

Arnold, V., Clark, N., Collier, P.A., Leech, S.A., and Sutton, S.G. "The differential use and effect of knowledge-based systems explanations in novice and expert judgment decisions," *MIS Quarterly* (30:1) 2006, pp 79-97.

Arnold, V., Collier, P.A., Leech, S.A., and Sutton, S.G. "Impact of Intelligent Decision Aids on Experienced and Novice Decision-Makers' Judgments," *Accounting & Finance* (44:1) 2004b, pp 1 - 26.

Barr, S.H., and Sharda, R. "Effectiveness of decision support systems: development or reliance effect?," *Decision Support Systems* (21:2) 1997, pp 133-146.

Bell, D.E., Raiffa, H., and Tversky, A. "Descriptive, Normative and Prescriptive Interactions in Decision Making," in: *Chapter 1 in Decision Making: Descriptive, Normative and Prescriptive Interactions*, Cambridge University Press, Cambridge, 1988, pp. 9 - 32.

Bereiter, C., and Scardamalia, M. *Surpassing Ourselves: An inquiry into the nature and implications of expertise* Open Court, Chicago, 1993.

Blattberg, R.C., and Hoch, S.J. "Database Models and Managerial Intuition: 50% Model + 50% Manager," *Management Science* (36:8) 1990, pp 887 - 899.

Brown, D.L., and Jones, D.R. "Factors that Influence Reliance on Decision Aids: A Model and an Experiment," *Journal of Information Systems* (12:2) 1998, pp 75 - 94.

Chase, W.G., and Simon, H.A. "Perceptions in Chess," *Cognitive Psychology* (4) 1973, pp 55 - 81.

Collier, P.A., Leech, S.A., and Clark, N. "A validated expert system for decision making in corporate recovery," *International Journal of Intelligent Systems in Accounting, Finance & Management* (8) 1999, pp 75 - 88.

Connolly, T., and Thorn, B.K. "Predecisional Information Acquisition: Effects of Task Variables on Suboptimal Search Strategies," *Organizational Behavior and Human Decision Processes* (39) 1987, pp 397 - 416.

Connolly, T., and Wholey, D.R. "Information Mispurchase in Judgment Tasks: A Task-Drive Causal Mechanism," *Organizational Behavior and Human Decision Processes* (42) 1988, pp 75 - 87.

Davern, M.J. "Towards a Unified Theory of Fit: Task, Technology and Individual.," in: *Information Systems Foundations: Theory, Representation and Reality,* D.N. Hart and S. Gregor (eds.), The Australian National University E Press, Canberra., 2007, pp. 49-69.

Davern, M.J., and Parkes, A. "Incommensurability in Design Science: Which Comes First Theory or Artifact?," in: *Information Systems Foundations: Answering the unanswered questions about design research,* S. Gregor and S. Ho (eds.), ANU E Pres, Canberra, 2008.

Davis, F.D., and Kotteman, J.E. "User Perceptions of Decision Support Effectiveness: Two Production Planning Experiments," *Decision Sciences* (25:1) 1994, pp 57 - 78.

Davis, F.D., and Kotteman, J.E. "Determinants of Decision Rule Use in a Production Planning Task," *Organizational Behavior and Human Decision Processes* (63:2) 1995, pp 145 - 157.

DeSanctis, G., and Poole, M.S. "Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory.," *Organization Science* (5:2), 1994/05// 1994, pp 121-147.

Devaraj, S., and Kohli, R. "Performance Impacts of Information Technology: Is Actual Usage the Missing Link?," *Management Science* (49:3) 2003, pp 273 - 289.

Fildes, R., Goodwin, P., and Lawrence, M. "The design features of forecasting support systems and their effectiveness," *Decision Support Systems* (42:1) 2006, pp 351-361.
Goodhue, D.L. "Development and measurement validity of a task-technology fit instrument for user evaluations of information systems," *Decision Sciences* (29:1) 1998, pp 105-138.
Goodhue, D.L., and Thompson, R.L. "Task-technology fit and individual performance," *MIS Quarterly* (19:2) 1995, pp 213-236.
Jiang, J.J., and Klein, G. "Side effects of decision guidance in decision support systems," *Interacting with Computers* (12) 2000, pp 469 - 481.
Kachelmeier, S.J., and Messier, W.F. "An Investigation of the Influence of a Nonstatistical Decision Aid on Auditor Sample Size Decisions," *The Accounting Review* (65:1) 1990, pp 209 - 226.
Kamis, A., Koufaris, M., and Stern, T. "Using an Attribute-Based Decision Support System:for User-Customized Products Online An experimental Investigation," *MIS Quarterly* (32:1) 2008, pp 159 - 177.
Kaplan, S.E., Reneau, J.H., and Whitecotton, S.M. "The Effects of Predictive Ability Information, Locus of Control, and Decision Maker Involvement on Decision Aid Reliance," *Journal of Behavioral Decision Making* (14) 2001, pp 35 - 50.
Leech, S.A., Collier, P.A., and Clark, N. "A generalized model of decision-making processes for companies in financial distress," *Accounting Forum* (23:2) 1999, pp 155 - 174.
Leech, S.A., Collier, P.A., Sutton, S.G., and Arnold, V. "Impact of intelligent decision aids on human knowledge acquisition," Australian Research Council Discovery Project Grant DP 0344241.
Limayem, M., and Desanctis, G. "Providing Decisional Guidance for Multicriteria Decision Making in Groups," *Information Systems Research* (11:4) 2000, pp 386 - 401.
Mahoney, L.S., Roush, P.B., and Bandy, D. "An investigation of the effects of decisional guidance and cognitive ability on decision-making involving uncertainty data," *Information & Organization* (13) 2003, pp 85 - 110.
Markus, M.L., and Silver, M.S. "A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole's Concepts of Structural Features and Spirit.," *Journal of the Association for Information Systems* (9:10), 2008/10// 2008, pp 609-632.
Miller, G.A. "The Magical Number Seven, Plus or Minus Two:
Some Limits on our Capacity for Processing Information," *The Psychological Review* (63:2) 1956, pp 81-97.
Montazemi, A.R., Wang, F., Nainar, S.M.K., and Bart, C.K. "On the effectiveness of decisional guidance," *Decision Support Systems* (19) 1996, pp 181 - 198.
Moreau, É.M.-F. "The impact of intelligent decision support systems on intellectual task success: An empirical investigation," *Decision Support Systems* (42:2) 2006, pp 593-607.
Newell, A. "Foundations of Cognitive Science," in: *Unified Theories of Cognition*, Harvard University Press, Cambridge, 1990, pp. 42 - 106.
Parikh, M., Fazlollahi, B., and Verma, S. "The Effectiveness of Decisional Guidance: An Empirical Evaluation," *Decision Sciences* (32:2) 2001, pp 303 - 331.
Salthouse, T.A. "Expertise as the circumvention of human processing limitations," in: *Toward a general theory of expertise - prospects and limits,* K. Ericsson and J. Smith (eds.), Cambridge University Press, New York, 1991, pp. 286 - 300.
Silver, M.S. "Descriptive Analysis for Computer-Based Decision Support," *Operations Research* (36:6) 1988, pp 904 - 916.
Silver, M.S. "Decision Support Systems: Directed and Nondirected Change," *Information Systems Research* (1:1) 1990, pp 47 - 70.
Silver, M.S. "Decisional Guidance for Computer-Based Decision Support," *MIS Quarterly* (15:1) 1991, pp 105 - 122.
Tabachnick, B.G., and Fidell, S. *Using Multivariate Statistics*, (4th ed.) Allyn and Bacon, Boston, 2001.
Te'eni, D. "Designs that fit: An overview of fit conceptualizations in HCI," in: *Human-Computer Interaction and Management Information Systems - Foundations. Advances in Management Information Systems,* P. Zhang and D. Galletta (eds.), M. E. Sharpe., Armonk, NY, 2005.
Wilson, E.V., and Zigurs, I. "Decisional Guidance and end-user display choices," *Accounting, Management & Information Technology* (9) 1999, pp 49 - 75.