JOURNAL OF INFORMATION SYSTEMS
Vol. 17, No. 1
Spring 2003
pp. 63–83

The Effects of Exclusive User Choice of Decision Aid Features on Decision Making

Patrick R. Wheeler
University of Missouri–Columbia

Donald R. Jones
Texas Tech University

ABSTRACT: Decision Support Systems (DSS) frequently have multiple decision aid (DA) features, causing users to engage in exclusive choice behavior; i.e., choice between alternative DA features that results in one feature being used to the exclusion of all others. We hypothesize that: (1) users choose the least effective (least accurate) DA feature in certain predictability environments; (2) users choose the DA feature that they believe they are most competent with; and (3) choice between DA features improves performance compared to those assigned the same DA feature. We test these hypotheses in an experiment in which 164 participants act as loan officers who chose between two decision aids (a database aid and a regression aid). The results support our hypotheses. Users employed a choice heuristic that caused them to choose the least effective DA feature for the task more than or as often as the most effective DA feature. Results also indicate a positive relationship between perceived competence and DA feature choice, and the positive effect of DA choice. We conclude by describing the insights provided by the results into the heuristics of information technology choice.

Keywords: user choice; decision aids; decision support systems; competence; heuristics.

Data Availability: Data are available upon request.

I. INTRODUCTION

Accountants and other computer users must choose which features to utilize in their computers. Computer systems have become so versatile and user friendly that they now present the user with a myriad of options. Toolbars, task panes, and drop-down menus are everyday examples of the choice-rich environment confronting users. Although programs may allow the user to employ multiple features in a single work session, the very richness of the choice environment often results in users choosing to use only a subset of the available features. Users are thus responding to this rich environment by engaging in "exclusive choice," i.e., a choice between alternative features that results in one feature being used to the exclusion of all other features. Users may make exclusive choices for several reasons—time constraints, cognitive effort minimization, heuristics,

The advice and recommendations of Ram Sriram, Fred Jacobs, and Howard Schneider of the dissertation committee were invaluable. We are especially grateful to Vairam Arunachalam for providing us with numerous helpful comments. We are also grateful for helpful comments on an earlier draft of this paper at the University of Missouri–Columbia (February 2002) and from Dan Stone. We also thank two anonymous reviewers for their helpful comments.

habit, or the belief that additional tools will results in only marginal gains. Nonetheless, little is known about the nature of exclusive choice. To what extent, for example, is it rational? To what extent is it driven by heuristics that may lead to suboptimal performance?[1]

One environment in which accountants and accounting information users engage in exclusive user choice is that of decision support systems (DSS) containing multiple decision aid (DA) features. DSS are widely used in business, going under such names as online analytical processing (OLAP), software agents, business intelligence software, executive information systems (EIS), geographic information systems (GIS), executive support systems (ESS), group DSS, and knowledge discovery systems (Power 1997; Turban et al. 2001). One aspect that these systems share and that allows them to be highly versatile is the presence of multiple DA features. DSS typically include some mix of DA features that are model-driven, data-driven, communications-driven, document-driven, and knowledge-driven (Power 2001). Software designers and vendors have long recognized the difficulties involved in designing DSS with the proper mix of DA features, the goal being to provide neither too few nor too many features (Dix et al. 1993; Sprague and Carlson 1982).[2]

Research suggests that exclusive user choice of DA features can affect decision process and accuracy. Jones and Schkade (1995) found that when users have to choose which representation will be used for solving a problem, they make this choice early and heuristically. Dilla and Stone (1997) demonstrated that user choice of response formats impacts DSS usage. Prior research has not, however, investigated the effect of exclusive choice between multiple DA features in a DSS on user performance, specifically accuracy and choice strategies. Accordingly, this paper investigates the issue of how exclusive user choice affects decision aid usage; i.e., the accuracy and choice behavior of users provided with multiple DA features.

In a behavioral experiment, exclusive choice between two DA features in a DSS is *forced* on subjects via the design of the DSS in order to proxy for environmental and psychological factors that cause real-world users to engage in exclusive user choice. Our contention is not that systems would be designed to force exclusive choice (although this may be the best solution in some cases), but that these exclusive choices constantly occur in computer usage, that they impact user effectiveness (e.g., accuracy) and that, like many behavioral problems in IT usage, the solution may not be straightforwardly technological (i.e., a design issue).

We organized the remainder of this paper as follows. The next section reviews the literature on DSS and user choice. We then develop hypotheses concerning the impact of exclusive user choice on judgment quality and decision making. The subsequent section explains the experimental method. We then present the results. In the final section, we discuss limitations, contributions, and future research.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Of necessity, users of multiple DA features must engage in some type of choice behavior. Users must either choose: (1) to rely on all of the DA features available as fully as possible, (2) to rely on the DA features to varying degrees less than fully, or (3) to use one or more DA features to the

[1] Huber (1983, 575) predicted that "future DSS" would be "flexible, friendly, and [with] a variety of options," as they have now become. He further predicted that such systems could lead to lower performance if users were to either (1) choose features that reinforce preferred suboptimal cognitive styles and predispositions or (2) ignore features that supplement innate cognitive approaches because these features do not fit user propensities. He believed that the answer to this dilemma would not be found in "constraining the nature of the DSS design" (Huber 1983, 575), i.e., in eliminating options and user choice. Instead, users should be coached and trained, and users and designers should make informed choices in light of human cognitive limitations. Huber (1983) argued that implementing these solutions would require taking new directions in cognitive style research. Accordingly, this study is an attempt to provide users and designers with knowledge about the nature and consequences of one type of user choice.

[2] To address this problem, Microsoft, for example, is now marketing Visual Studio for Applications (VSA) specifically to allow organizations to customize their systems to fit users' particular needs in Web-based environments (Microsoft 2001). "You have plenty of choices for prepackaged ... applications ... but customizing them to conform to an organization's unique procedures is time-consuming and expensive." (See Microsoft 2001, 1.)

exclusion of the others. Case studies indicate that users engage in type (3) (exclusive user choice) and, consequently, do not always use DSS with multiple features optimally (Stabell 1983; Swisher 1996). Stabell (1983) found that several DA features in a portfolio management DSS were never used. Swisher's (1996) investigation of the Medicaid Management Information System (MMIS) DSS indicated that some features were used infrequently. Similarly, Silicon Graphic's Mineset™ allows users to choose from a menu of datamining techniques to analyze the data set and it is common to see users using the selected technique/feature exclusively for an extended period of time (Rathjens and Vanderberg 1998).

Researchers have concentrated on two areas of user choice in DSS. First, research has been done on the *extent* to which users choose to employ a *single* DA feature; i.e., decision aid reliance (Arkes et al. 1986; Ashton 1990; Brown and Jones 1998; Davis and Kotteman 1994; Dos Santos and Bariff 1988; Jones et al. 2001). This research, however, does not address the issue of exclusive choice between alternatives. The second stream of research has investigated different types of exclusive user choice in DSS, but not the choice between competing decision aids (Becker 1997; Jones and Schkade 1995; Dilla and Stone 1997; Whitecotton and Butler 1998). The studies in this second stream are important because they shed light on the general nature of exclusive user choice in DSS. They indicate that user choice is a significant type of behavior among IT users, although the results are somewhat mixed. In two studies (Jones and Schkade 1995; Whitecotton and Butler 1998), user choice had a predominantly negative effect on performance, while in the other two studies (Becker 1997; Dilla and Stone 1997) it had a primarily positive impact. However, these studies have important differences in both theoretical focus and experimental design from each other and from this study. Accordingly, the present study makes a contribution by investigating the impact of exclusive user choice between multiple DA features on decision making.

Hypothesis 1: Choice Heuristic Hypothesis

To the extent that decision makers choose rationally, choice should improve judgment quality (e.g., accuracy). However, choice may cause a decline in judgment quality if users choose inappropriately, which may occur if decision makers choose the DA feature using a choice heuristic. Heuristics tend to introduce biases in decision making because they are often used across diverse conditions for which they are not equally effective (Baron 1994; Kahneman et al. 1982).

Prior research indicates that the heuristic specific to choosing between DA features involves a tendency toward suboptimal use of information technology (IT) under a wide variety of circumstances. Arkes et al. (1986) and Ashton (1990) found that incentives that were normally effective at improving judgment quality in unaided conditions became ineffective, if not detrimental, in conditions with mechanistic aids. Arnold and Sutton (1998) find evidence that users become overly dependent upon technology-based decision aids. Peterson and Pitz (1986) conversely found users rejecting advice from models based on the users' own implied decision-making model when that model is automated.

The heuristic suggested by this research is one in which human cognition, adapted toward certain responses to decision-making problems under nontechnological situations, becomes dysfunctional by the relatively recent addition of IT, such as decision aids. Modularity theory in cognitive science postulates that the mind confronts reality with a finite number of specialized modules consisting of various decision-making and problem-solving heuristics (Fodor 1983). Because such modules and heuristics develop slowly and meticulously, there is probably not currently a fully functional module or heuristic for incorporating modern IT effectively into human cognition (Buss 1998). The choice heuristic we are suggesting is, therefore, one in which, when confronted with choices between multiple IT features, the "rule of thumb" humans use is either: (1) to resist the technology or (2) to inadequately incorporate it into an incompletely developed module/heuristic or into one developed for other types of problems. The first reaction (resistance) helps explain decision aid underreliance. The second reaction (inadequate incorporation) is the one predicted for the situation in the current study because a choice between two technologies forces the inclusion of technology, no matter how ineffectively.

We hypothesize that users employ a heuristic for choosing between DA features and subsequently applying the chosen DA feature. We also hypothesize that exclusive user choice will have differing effects on judgment (e.g., accuracy) depending on the task environment because heuristics are generally not equally effective over diverse conditions. When there is an interaction between the task environment and the DA type so that one DA feature performs better in one condition, while another DA feature performs better in another condition, then it is hypothesized that the presence of a choice heuristic will result in the least effective DA feature being chosen in some of the task environments. For example, if participants use a heuristic for choice so that they choose the same DA feature under all conditions, the DA effectiveness reversal (due to the interaction of DA type with task environment) will result in the least effective DA feature being chosen in one of the two environments. Another possible heuristic suggested by Hoch and Schkade (1996) is that participants will choose the DA type that allows them to utilize their strongest cognitive ability for the most demanding environment. Thus, in a more cognitively demanding low-predictability environment, participants are expected to choose a database aid over a regression aid because of the former's support of users' relative strength in pattern matching. Nonetheless, the chosen decision aid may be the least effective one when these DA features are assigned in experimental conditions (Hoch and Schkade 1996). Either of these heuristics would result in choosing the least effective DA feature in at least one of the two environmental predictability conditions. Thus, given two DA features (1 and 2) and two predictability environments (high and low), and assuming that DA type 1 (2) is more effective than DA type 2 (1) for the high-(low-) predictability environment, H1 may be stated as:

> **H1:** The DA type chosen will be the least effective DA type for at least one of the predictability environments.

Hypothesis 2: Perceived Competence with DA Features Hypothesis

A weak assumption of rationality is that users will choose the DA features that they believe they are most competent at using, although this belief may be wrong. This expectation is supported by cognitive fit theory, which states that efficiency and effectiveness increase as the three-way match among (1) the problem representation, (2) the problem-solving task, and (3) the user's problem-solving skill set increases (Vessey 1991; Vessey and Galletta 1991). Moreover, the theory postulates that decision makers correctly perceive improvements in cognitive fit (Vessey and Galletta 1991). From cognitive fit theory we argue that users will choose alternatives they perceive to increase their competence with DA features; i.e., the tools that best match their self-assessed problem-solving skills. This prediction is also supported by Jones and Schkade's (1995) results, which show that decision makers tend to choose the problem representation with which they have the most experience.

Thus, the second hypothesis predicts that the higher the relative self-assessed competence with DA feature 1 over DA feature 2, the more likely the decision maker is to choose DA feature 1 over DA feature 2, assuming the same task and same environmental predictability. Thus, the second hypothesis may be stated as:

> **H2:** The number of times a user chooses a DA feature is positively correlated with the user's perceived competence with that DA feature.

Hypothesis 3: Choice Usage versus Required Usage Hypothesis

Even when a choice heuristic causes suboptimal performance with multiple DA features (as in H1), there are still reasons to expect that, *under certain conditions*, exclusive user choice will be beneficial. Specifically, we predict that those who have chosen a certain DA feature will outperform those who have been randomly assigned the same DA feature. This hypothesis is conditional in that it looks at each DA feature alone and does not compare the effectiveness of different DA features to one another.

An overall improvement in judgment quality from exclusive user choice is based on the expectation that users will choose so as to take advantage of the users' unique capabilities. This assumes that users can correctly assess their abilities, at least partially. Thus, users allowed to choose between DA features will find a better fit of DA feature, task, and skill set than users randomly assigned a DA feature. The gain from choice will be primarily from the users choosing DA features more in line with their personal characteristics (e.g., skills or cognitive style) than the alignment between DA features and users' capabilities that occurs from random assignment.

Thus, the third hypothesis predicts that participants who choose a DA feature will show better judgment quality than those who are assigned that same DA feature, given the same task and the same environmental conditions.

H3: Users that choose a DA feature show greater judgment accuracy than users that are assigned use of the same DA feature, *ceteris paribus*.

III. METHOD

Experimental Design and Task

Participants assumed the role of bank loan officers and evaluated commercial loan applicants using a computerized DSS with multiple (two) DA features. We randomly divided participants into four groups (see Table 1). We assigned participants in two groups to one of the two DA features, with the other DA feature deactivated. In the third group, participants choose between the two DA features. For

TABLE 1
Experimental Design

Condition	Environmental Predictability	Choice Condition	Number of Participants for Testing Power[a]	Actual Number of Participants	Number of Trials[b]
1	Low and High	Choose regression aid or database aid	50	54	20
2	Low and High	Assigned regression aid (no choice)	25	29	20
3	Low and High	Assigned database aid (no choice)	25	25	20
4	Low and High	Unaided (no choice)	25	28	20

a For the significant results, the observed testing power (i.e., the chance of correctly rejecting a false null using alpha = 0.05) ranged from 64 percent to 99 percent. For H3, the observed testing power was 99 percent. For H1, the observed testing power ranged for 68 percent to 88 percent.

b Order of environmental predictability was counterbalanced across treatments. Each participant had ten trials in each of the two environmental predictability conditions (high and low).

each trial, users made a choice that activated the chosen DA feature and deactivated the nonchosen one. We forced exclusive choice between the two DA features on subjects (via the design of the DSS) in order to proxy for environmental and psychological constraints imposed on the user, normally external to the system's design (e.g., time constraints, opportunity costs, cognitive effort minimization, heuristics and beliefs about competence). The fourth group had access to neither DA feature (unaided).

The task consisted of predicting credit rating estimates of bank loan applicants five years in the future. Participants used a scale of 0–100 to make their estimates and were informed that 0 represents the lowest credit rating and that 100 represents the highest rating. The following accounting-based information was provided to the participants for each applicant:

(1) *debt ratio*: total assets divided by total debt (range 1 to 3)
(2) *cash flow*: income before taxes and interest divided by interest expense (range 1 to 8)
(3) *revenue trend*: the number of quarters out of the prior 20 that revenues increased (range 8 to 20)
(4) *applicant's location*: Midwest, East Coast, or West Coast (indicative of regions of differing economic conditions)

These ratios were selected based on research in bankruptcy prediction (Dietrich and Kaplan 1982; Hoch and Schkade 1996; Marais et al. 1984).

Environmental predictability is a primary indicator of the information content of the task environment (Libby 1981; Ashton 1982). It provides information concerning the degree to which the predictor variables may be used to estimate the outcome variable. In this study, we operationalized environmental predictability as the correlation between the "actual" (i.e., simulated) credit rating of an applicant and a predicted credit rating for the same applicant from a regression model based on a database of prior applicants. We simulated applicant data so that we could control environmental predictability (Hoch and Schkade 1996). We varied environmental predictability through the error term in the regression model and determined the error terms by pilot testing the regression models to verify that subjects would perceive a significant difference between the two environments.

Using applicant information provided, along with any information from the DA feature (if available), participants entered 20 task judgments into the DSS interface, ten in the high-predictability condition, and ten in the low-predictability condition. Users completed each applicant credit rating before proceeding to the next. We randomly assigned participants to the presentation order of the 20 tasks. Some subjects received ten high-predictability tasks followed by ten low-predictability tasks, while other subjects received the opposite order. Order was analyzed statistically and had no effect on the hypothesis testing results. Table 1 shows the experimental design.[3]

Decision Support

The two DA features were: (1) a regression model estimate of the credit rating and (2) a historical database of prior applicants. The historical database DA feature contained a random selection of 20 prior applicants and displayed the three accounting ratios, location, and credit rating of each applicant. We informed participants that this credit rating is the actual credit rating that ensued five years from the date of application. The regression prediction DA feature consisted of only the three accounting ratios and provided a credit rating estimate of the applicants five years in the future. The applicant's location was not included in the model. This absence allowed for the desired interaction reversal between DA type

[3] Our design builds on that of Hoch and Schkade (1996). However, Hoch and Schkade (1996) did not examine choice in their experiment. Subjects were provided either one or both DA features, and in the latter case, subjects were not required to exclusively choose between the two DA features, as in the present study. Hoch and Schkade (1996) did not analyze those provided with both DA features to see if exclusive user choice was occurring. Thus, in Hoch and Schkade (1996), it is not clear to what extent the results from subjects provided with both DA features were due to (1) the subjects full/partial reliance on both features or (2) the subjects use of one feature only, with the other feature ignored. In order to test for exclusive user choice, we made several modifications to Hoch and Schkade's (1996) design so that users would have to choose in an exclusive manner.

and task environment, following Hoch and Schkade (1996). We informed participants in the written instructions that this variable is missing from the regression model.

Use of a missing variable was also meant to create the perception in the participants that there are advantages and disadvantages to choosing either DA feature so that choice would not appear to be trivial. The regression aid has the mathematical predictive power for which regression analysis is known. However, the historical database aid has a more complete set of information than the regression aid because of the missing variable (location) in the regression model. Accordingly, experimental design made it possible to create a situation in which subjects could do better with the regression aid in the low-predictability environment, while doing better with the database aid in the high-predictability environment. Furthermore, these two DA features capture different aspects of cognition; i.e., computation and information acquisition (Hoch and Schkade 1996).

The linear model used to simulate the data is:

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + \varepsilon \qquad (1)$$

where x_1, x_2, x_3, and x_4 are the three financial ratios and location, ε is the error term, and y is the applicant's credit rating. For the b values, the financial ratios were equally weighted, while location was weighted higher than the ratios. The unequal weighting created a noticeable difference between the regression prediction (without location) and the case-based examples (with location) so that users would perceive a significant difference between the two DA features. The values for the variables were randomly generated from uniform distributions. The error terms were randomly generated from normal distributions with means of zero. The standard errors for the high- and low-predictability environments are 0.39 and 0.64, respectively. The y values ranged from zero to 100.

The simulation procedures resulted in two populations of 240 applicants: one in low predictability and one in high predictability. Each population was separated into two samples, a model-building sample used to construct the regression aid and a hold-out sample from which the 20 applicants to be evaluated by the participants were randomly drawn. For each model-building sample, the three accounting ratios were regressed on the y values to obtain the regression aid equation used to calculate the regression aid's estimate of clients' credit ratings. Because all deviations from the linear model are deliberately generated, precise calculations for judgment performance are possible.[4]

Participants in all experimental conditions interacted with Java-implemented interfaces. Screen captures of the interfaces are shown in Figures 1–4. The unaided condition interface displayed an applicant's three financial ratios, location, and environmental predictability (Figure 1). The assigned database-aided condition interface displayed an applicant's three financial ratios, location, and environmental predictability, and an enabled database DA feature showing 20 cases of randomly selected past applicants (Figure 2). The assigned regression-aided condition interface displayed an applicant's three financial ratios, location, and environmental predictability, and an enabled regression aid's estimate of the applicant's credit rating (Figure 3). For both of the assigned DA feature interfaces, the unassigned DA feature was shown but was disabled. We did this disabling to make it clear to the subjects that an alternative DA feature is available, but that choice of that feature is not allowed. The choice condition interface displayed an applicant's three financial ratios, location, and environmental predictability, and enabled regression and database DA features at the start of each new task (Figure 4). Once a subject chose between the two DA features, the DA feature not chosen was disabled. Choice between DA features was repeated for each task.

[4] The regression aid (with the location variable missing) for the high-predictability environment is significant ($p < 0.001$) and has an adjusted R^2 of 0.101. The regression aid (with the location variable missing) for the low-predictability environment is significant ($p = 0.019$) and has an adjusted R^2 of 0.039.

FIGURE 1
Interface for Unaided Condition

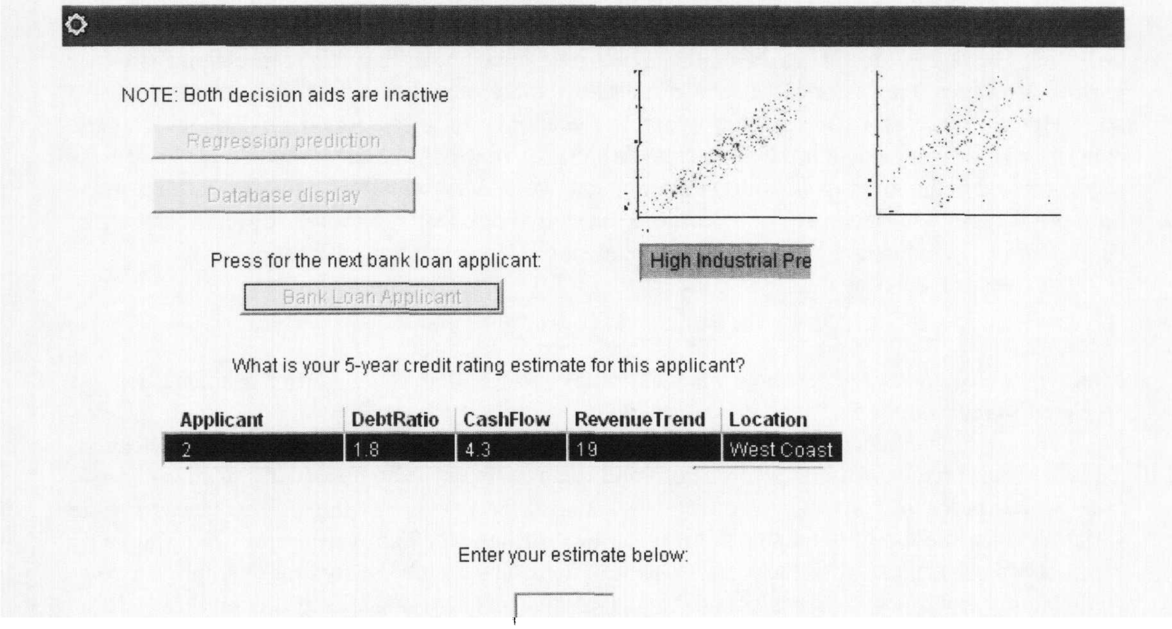


FIGURE 2
Interface for Assigned Database DA Feature Condition

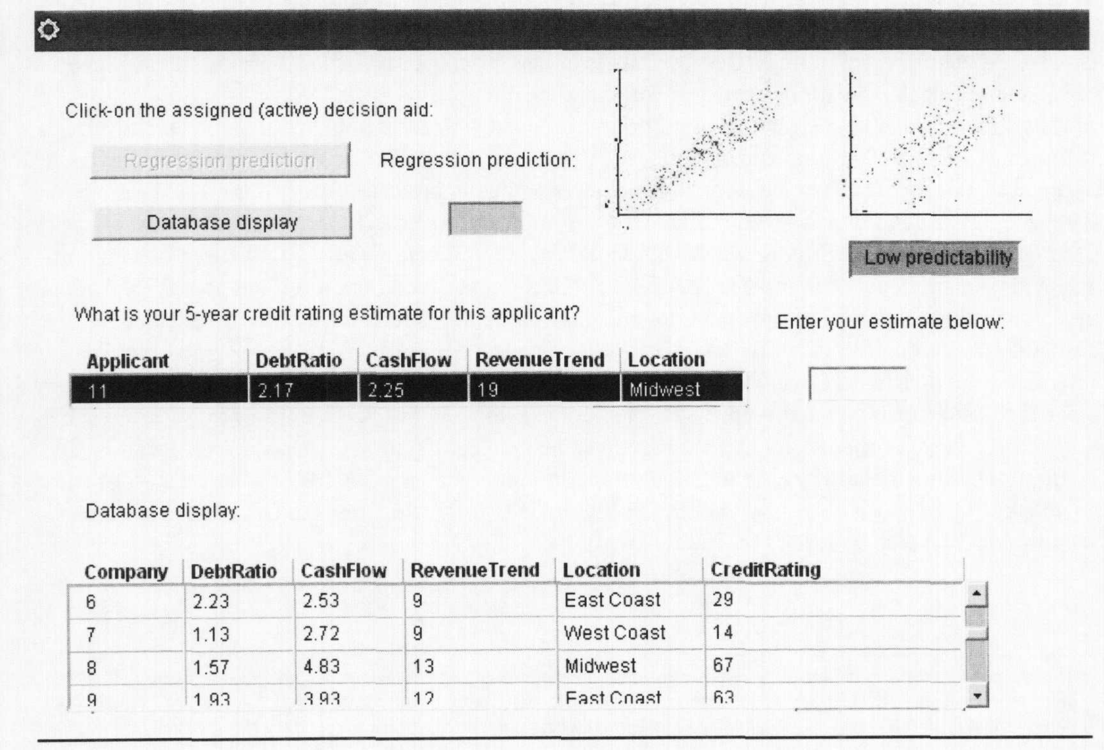


FIGURE 3
Interface for Assigned Regression DA Feature Condition

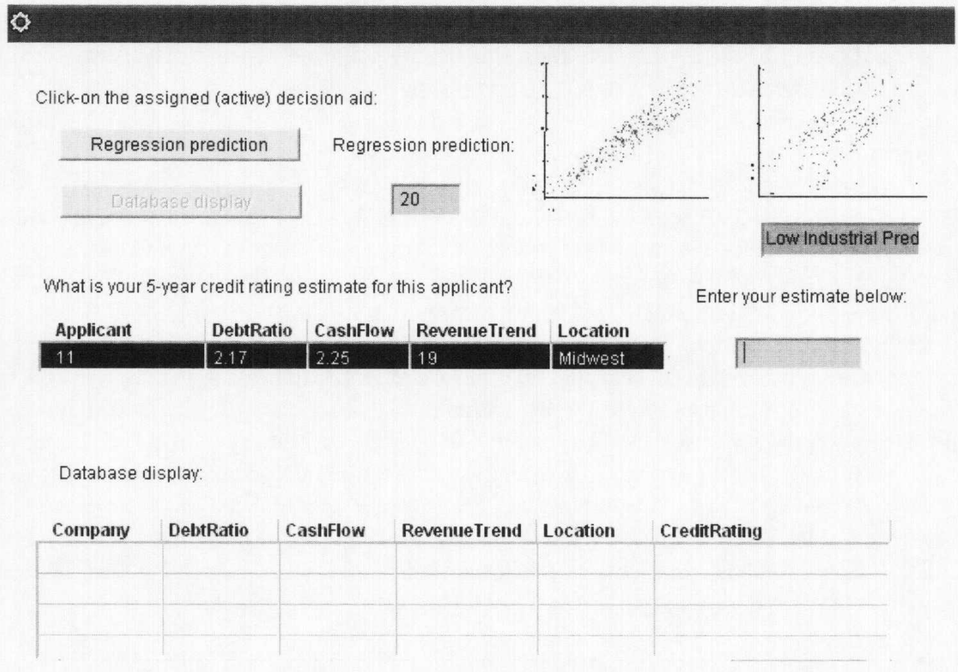
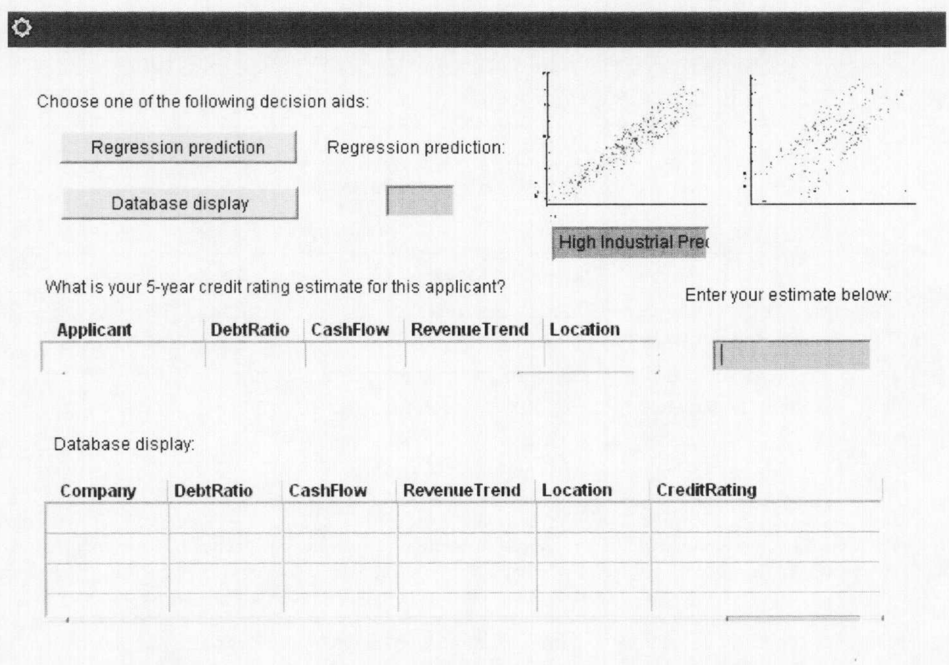


FIGURE 4
Interface for Choice between DA Features Condition



Participants and Procedures

Participants were M.B.A. students at a large state university enrolled in introductory accounting courses. We estimated that 125 subjects would be required to provide adequate statistical power (see Table 1 notes). One hundred sixty-four M.B.A. students participated, of which 136 were used in analysis. The deletion of the 28 subjects from the sample occurred because of software errors (n = 23) or inaccurate performance of key tasks (n = 5).[5]

In a post-test questionnaire, participants provided demographic information about the following items: (1) gender; (2) age; (3) part-time work experience; (4) full-time work experience; (5) bank experience; (6) training in statistics; and (7) training in regression analysis. Table 2 presents the demographic results. ANOVA tests indicated that there were no significant differences in the demographic variables among the four treatment groups at a 0.05 significance level (p-values range from 0.117 to 0.927). Furthermore, regressions of the accuracy dependent variable (mean absolute accuracy) with the demographic predictor variables were not significant for a 0.05 significance level (p-values range from 0.084 to 0.958).

The experiment proceeded in four phases. First, we gave participants a brief oral introduction and written instructions appropriate to the experimental condition. We informed participants that those performing in the top half would be included in a single $75 lottery. Second, all participants performed ten practice trials (five with each DA feature) on computers to familiarize themselves with the DSS and the task. Third, the main testing occurred during which participants performed the 20 experimental trials. Fourth, a post-test questionnaire collected demographic data and self-assessments of decision aid usage. Participants performed all phases during one computer laboratory session, with completion times ranging from 20 to 60 minutes.

Measures

The dependent variables are (1) judgment performance; i.e., accuracy, (2) perceived competence with each DA feature, and (3) DA choice percentage.

Correlation and mean absolute accuracy (MAA) measure the accuracy of the participants' judgments (cf. Ashton 1982; Hoch and Schkade 1996; Libby 1981). Correlation is the Pearson correlation between the judgment and the benchmark from the simulated data. MAA is calculated as the absolute difference between each judgment and its respective benchmark subtracted from 100. For both dependent variables, a higher value indicates greater accuracy.[6] In the choice condition, each participant had

TABLE 2
Summary of Demographic Information

Variable	Statistics	
Age:	Mean = 28.8 years	Range = 22–47 years
Part-time work experience:	Mean = 2.9 years	Range = 0–15 years
Full-time work experience:	Mean = 6.2 years	Range = 0–26 years
Bank experience:	5% with prior experience	
Training in statistics:	87.5% with prior experience	
Training in regression analysis:	66% with prior experience	
Gender:	61% males, 39% females	

[5] Twenty-three of the 28 subjects dropped had no output file because of software problems. The remaining five did not perform the experiment correctly: two did not complete the questionnaire and three entered judgments twice.

[6] The correlation and MAA measures focus on different aspects of accuracy. The correlation measure indicates strength of the relationship between the judgments and the benchmark; the MAA shows the extent of difference between judgments and the benchmarks. The most informative approach is to report analyses using both measures (e.g., Ashton 1990).

performance measures calculated for both DA features. Thus, choice participants had correlation and MAA measures calculated for both the regression DA feature and the database DA feature.

Perceived competence with DA features is computed from self-reported information from the post-test questionnaire. Participants evaluated their competency with each DA feature by responding to the following two statements using a five-point Likert scale:

- "Using the database display made me feel more competent."
- "Using the regression prediction made me feel more competent."[7]

DA choice percentage is determined from the number of times a DA feature was chosen in all choice scenarios. For example, if tool A is chosen 12 times in 20 trials, the choice percentage equals 60 percent, i.e., tool A is chosen 60 percent of the time.

IV. RESULTS

Descriptive Statistics and Manipulation Check on the Unaided Group

Table 3 presents descriptive statistics using all aided and unaided conditions and both levels of environmental predictability. Means are shown for subjects who either chose or were assigned the database DA feature (Panel A: $n = 61$); subjects who either chose or were assigned the regression DA feature (Panel B: $n = 68$); and for unaided subjects (Panel C: $n = 28$).

We used ANOVAs comparing aided and unaided groups to examine the effectiveness of the decision aids. In the high-predictability environment, unaided subjects did significantly worse than those assigned either the regression aid or the database aid ($F = 6.78$, $p = 0.01$ for MAA; $F = 7.60$, $p = 0.007$ for Correlation). In the low-predictability environment, there was no significant difference between the aided and unaided groups ($F = 1.29$, $p = 0.25$ for MAA; $F = 0.204$, $p = 0.65$ for Correlation). These results indicate that the decision aids can be effective under certain conditions (i.e., high-predictability environment).

Testing of H1 (Choice Heuristic Hypothesis)

Hypothesis 1 was tested in two parts. First, we tested for an interaction between environmental predictability and the accuracy of the two DA types. Second, we tested whether the DA type chosen was the DA type most effective for the particular environment.

Testing the First Part of H1

A necessary condition for testing H1 is that the two DA types perform differently in the two predictability environments. To test for this interaction, we performed a repeated measures ANOVA on the choice group and those assigned decision aids. We tested the two groups separately because of constraints regarding repeated measures testing; i.e., for the choice group, DA type is a within-subject factor, while DA type is a between-subject factor for the assigned groups. Table 4 shows the results of these tests run with perceived competence with DA features as a covariate to help assess whether subjects' self-assessed DA skills related to performance.[8] Main effects and the interaction were significant for all tests except for the choice group (measured by Correlation). These results indicated that the necessary interaction between task environment and DA type was present. Specifically, users did better with the regression aid in the low-predictability environment, but did better with the database aid in the high-predictability environment.

---

7 Separate questions were asked for each DA feature, instead of one question comparing the two DA features, because competency with one feature need not be related to competency with the other. Thus, two questions allow for separate competency measures for each DA feature. Asking the questions after the experiment avoided sensitizing the participants to this aspect of the study and minimized any demand effect.

8 The tests were also run without perceived competence as a covariate. The results were qualitatively equivalent.

TABLE 3
Descriptive Statistics

Panel A: Participants Using Database Decision Aid: Choice versus Assigned[a]
Sample size (n = 61): Choice group = 36; Assigned group = 25

	Pearson Correlation			MAA (Mean Absolute Accuracy)		
	Low-Predictability Environment	High-Predictability Environment	Low- and High	Low-Predictability Environment	High-Predictability Environment	Low- and High
Choice	.40	.66	.53	67.1	79.0	73.0
Assigned	.22	.62	.42	64.4	77.9	71.1
Choice and Assigned	.31	.64	.47	65.7	78.4	72.1

Panel B: Participants Using Regression Decision Aid: Choice versus Assigned[a]
Sample size (n = 68): Choice group = 39; Assigned group = 29

	Pearson Correlation			MAA (Mean Absolute Accuracy)		
	Low-Predictability Environment	High-Predictability Environment	Low- and High	Low-Predictability Environment	High-Predictability Environment	Low- and High
Choice	.34	.35	.35	69.8	69.4	69.7
Assigned	.14	.15	.15	69.9	67.6	68.6
Choice and Assigned	.24	.25	.25	69.8	68.5	69.1

Panel C: Participants Not Provided a Decision Aid Feature
Sample size (n = 28)

	Pearson Correlation			MAA (Mean Absolute Accuracy)		
	Low-Predictability Environment	High-Predictability Environment	Low- and High	Low-Predictability Environment	High-Predictability Environment	Low- and High
Unaided	.05	.18	.12	68.8	67.8	68.3

[a]In the choice condition, each participant has correlation and MAA measures of accuracy calculated for both the regression DA feature and the database DA feature.

Testing the Second Part of H1

We next tested whether the DA type chosen is the least effective DA type for at least one of the environments. Table 5 shows the means of the choice percentages by environmental predictability and the DA feature chosen, and the results of the repeated measures ANOVA. Three of the four differences, along with the interaction, were significant. Figure 5 presents the choice percentages from Table 5; it illustrates a reversal effect in which subjects were choosing different DA features in different environments[9] and choosing the least effective DA feature for at least one predictability environment, as predicted by H1. Specifically, subjects chose the least effective DA feature more

[9] The repeated-measures within-subject ANOVA tests of the two DA features were both significant, as shown in Table 5 (p-values of 0.005 for choosing the regression aid and 0.010 for choosing the database aid). This suggests a crossover effect, as graphically illustrated in Figure 5; i.e., as environmental predictability decreased, there was a significant increase in choosing the database aid and a significant decrease in choosing the regression aid. However, the point at which choice was measured for the low-predictability environment revealed no significant differences in choice between the two DA features. This may indicate that (1) the low-predictability environment measures needed to be made a lower point to show a significant difference or (2) that there was a ceiling effect at this point such that there is never a complete reversal in the crossover.

TABLE 4
Hypothesis 1 Test of DA Type and Environmental Predictability Interaction Effect on Accuracy Measures

Variable	F-statistic	Significance[c]
Testing of Choice Group[b] Using Mean Absolute Accuracy Measure		
DA Type	7.276	.013
DA Type × Competence[a]	5.440	.028
Environmental Predictability	14.498	.001
Environmental Predictability × Competence[a]	7.904	.010
DA Type × Environmental Predictability	5.248	.031
DA Type × Environmental Predictability × Competence[a]	1.002	.327
Testing of Choice Group[b] Using Correlation Measure		
DA Type	8.971	.011
DA Type × Competence[a]	.304	.592
Environmental Predictability	.454	.513
Environmental Predictability × Competence[a]	.023	.881
DA Type × Environmental Predictability	.524	.483
DA Type × Environmental Predictability × Competence[a]	6.622	.024
Testing of Assigned Group[b] Using Mean Absolute Accuracy Measure		
DA Type	4.079	.049
Competence[a]	0.026	.873
Environmental Predictability	39.181	.000
Environmental Predictability × Competence[a]	0.235	.630
DA Type × Environmental Predictability	68.774	.000
Testing of Assigned Group[b] Using Correlation Measure		
DA Type	40.259	.000
Competence[a]	0.317	.576
Environmental Predictability	32.797	.000
Environmental Predictability × Competence[a]	0.228	.635
DA Type × Environmental Predictability	31.539	.000

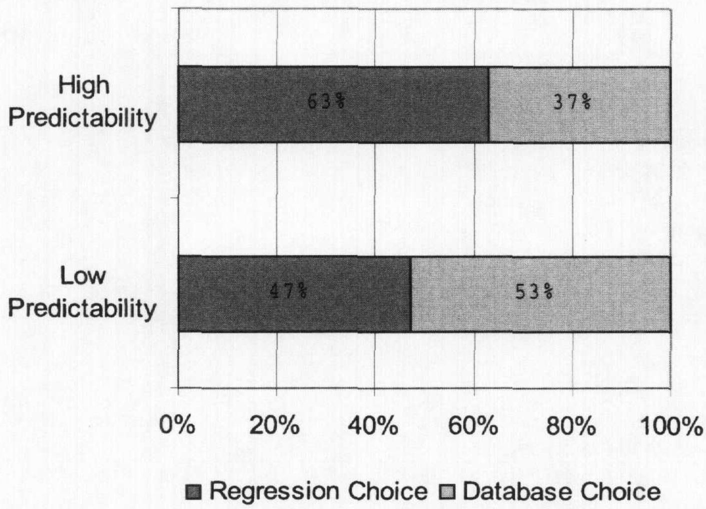
[a] Test results are shown with perceived competence with DA feature as a covariate. The tests were also run without the covariate with the results qualitatively the same.
[b] For the choice group, all variables are within subject. For the assigned groups, DA type is between subjects and environmental predictability is within subject.
[c] All significant results are in the predicted directions. (See Table 3 for means.)

TABLE 5
Hypothesis 1 Test of DA Choice Percentage of DA Type and Environmental Predictability[a]

	Low Predictability	High Predictability	F-value (p-value)
Regression Choice	47%	63%	8.396 (.005*)
Database Choice	53%	37%	8.390 (.010*)
F-value (p-value)	.368 (.547)	9.053 (.004*)	Interaction 8.400 (.005*)

* indicates significance at $p < 0.05$ using ANOVA.
[a] Regression Choice and Database Choice are the percentage that the respective DA feature was chosen in all choice scenarios (i.e., the number of times the DA feature was chosen out of the total of 20 trials). Low Predictability and High Predictability are the two environmental predictability conditions.

FIGURE 5
Hypothesis 1 Choice Percentage by Task Environment and DA Type



The horizontal axis shows the percentage that a DA feature was chosen in all choice scenarios (i.e., the number of times the DA feature was chosen out of the total of 20 trials). The vertical axis shows the two environmental predictability conditions.

often than the most effective DA feature in the high-predictability environment (a significant difference of 63 percent versus 37 percent for $p < 0.05$, respectively). In the low-predictability environment, the least and most effective DA features were chosen equally (53 percent versus 47 percent respectively, but not significant for $p < 0.05$).

Testing of H2 (Perceived Competence with DA Features Hypothesis)

Hypothesis 2 states that DA choice will be correlated with perceived competency. We conducted Pearson correlation tests (two-tailed) of H2 on the choice group. The 0.453 correlation between perceived competency with the regression aid and choice percentage for the regression DA feature was significant ($p = 0.001$). The 0.290 correlation between perceived competency with the database aid and choice percentage for the database DA feature was also significant ($p = 0.034$). Thus, H2 was supported. Furthermore, the –0.210 correlation between the perceived competency with the regression aid and the perceived competency with the database aid was not significant ($p = 0.120$), indicating that participants viewed the two types of tool competency as independent.

Testing of H3 (Choice Usage versus Required Usage Hypothesis)

We tested H3 with ANOVAs using one-tailed tests because directions were predicted for the dependent variables. In cases where data failed the Levene test for equal variances ($p > 0.05$), we transformed the data using the natural log (indicated in Table 6). All transformed data passed the Levene test. Table 6 presents results of testing H3. As in H1, we conducted the tests with perceived competence with DA features as a covariate to help assess whether subjects' self-assessed DA skills were related to performance.[10] When we combined environmental predictability conditions for testing, those who chose the DA feature had significantly better performance ($p < 0.05$) than those

[10] The tests were also run without perceived competence as a covariate with the same results qualitatively except for Combined Regression using Mean Absolute Error as the dependent variable. In this test, the p-value without competence covariate is 0.06 (versus 0.049 with the competence covariate).

TABLE 6
Mean Measures and Tests of Hypothesis 3

Environmental Predictability	DA Feature	DA Feature Chosen versus Assigned: Chosen	DA Feature Chosen versus Assigned: Assigned	p-value (one-tailed): With Competence as Covariate[a,b]
Correlation Dependent Measure				
Combined	Database	.329	.314	.482
	Regression	.251	.103	.048
Mean Absolute Accuracy Dependent Measure				
Combined	Database	70.3	71.1	.345
	Regression	70.5	68.6	.049
Correlation Dependent Measure				
High	Database	.657	.615	.325
	Regression	.243	.146	.060
Low	Database	.398	.260	.002
	Regression	.326	.144	.008
Mean Absolute Accuracy Dependent Measure				
High	Database	79.0	77.9	.355
	Regression	71.2	67.6	.028
Low	Database	67.1	64.4	.113
	Regression	70.1	69.5	.219

Correlation is the Pearson correlation between the judgment and the benchmark from the simulated data. Mean Absolute Accuracy is the absolute difference between each judgment and its respective benchmark subtracted from 100. For both variables, a higher value indicates greater accuracy.

[a] Test results are shown with perceived competence with DA feature as a covariate. The tests were also run without the covariate with the results qualitatively the same except for Combined Regression using Mean Absolute Accuracy as the dependent variable. In this test, the p-value without competence covariate is 0.06.

[b] All tests of the regression DA feature were on data transformed using the natural log.

who were assigned the same DA feature in two of the four tests. When we analyzed environmental predictability conditions separately, results were significant in three of the eight tests and marginally significant ($p < 0.10$) in one test. Thus, there was partial support for H3.

Post Hoc Analysis of H3

Further analysis investigated how perceived competence could improve performance when all else is equal. Our *post hoc* analysis was consistent with Becker's (1997) findings that user choice of DA model inputs is positively associated with an increase in motivation to use the DA feature. In this study's post-test questionnaire, subjects were asked how "committed" and "involved" they felt toward the two DA features, for a total of four questions. As shown in Table 7, the responses to the four commitment and involvement statements were significantly and positively correlated to the choice percentage variables of their respective DA features.

These results indicate that although people were choosing the DA feature that was not best for the task, they still outperformed those randomly assigned the same DA feature because of motivational factors. Motivation to use a DA feature leads to increased effort in applying the DA feature to the task, which may lead to increased accuracy (Becker 1997).

TABLE 7
Post Hoc Analysis of the Effect of Motivational Factors on DA Feature Choice

Post-Test Questionnaire Statement[a]	Correlation of Question Responses to Choice Percentage for Regression Aid	Post-Test Questionnaire Statement[a]	Correlation of Question Responses to Choice Percentage for Database Aid
"Using the regression prediction made me feel a sense of commitment."	0.329 p = 0.008**	"Using the database display made me feel a sense of commitment."	0.393 p = 0.002**
"Using the regression prediction made me feel a sense of involvement."	0.322 p = 0.009**	"Using the database display made me feel a sense of involvement."	0.407 p = 0.001**

** p-values based on Pearson correlation tests. Tests were conducted on the choice group (n = 54).
a The statements shown are with the actual wording used in the post-test questionnaire, with responses on a 1–5 Likert scale.

V. CONCLUSIONS

Discussion of Results

Tests of H1 investigated whether choice is uniformly beneficial to judgment accuracy under all conditions. We predicted that exclusive user choice would be made using a heuristic and would, therefore, have differing effects on judgment in different task environments (Baron 1994; Tversky and Kahneman 1974). The results from the first step in testing H1 indicated that in the low-predictability environment, regression aid users were more accurate than database aid users, while in the high-predictability environment, the situation reversed, with database aid users more accurate. We designed this interaction between DA type and task environment into the experiment in order to have the conditions necessary for investigating the nature of the choice heuristic.

Results for the second step in testing H1 indicated that participants were not predominantly choosing the DA feature that was most effective for the environment. In the high-predictability environment, participants chose the regression aid more often, although the database aid was more accurate in this environment. In the low-predictability environment, users chose the database aid as often as the regression aid, although the regression aid was more effective for that environment.

The results of testing H1, while supportive of the hypothesis, did not suggest the presence of a "one size fits all" heuristic. Users could have employed a simple choice heuristic in which they would choose a DA feature early in the problem-solving process and then stay with that choice thereafter (cf. Jones and Schkade 1995). Instead, the results indicated a more environmentally sensitive heuristic. Users reacted to changes in the information environment by changing their choice strategies, suggesting awareness of a relationship between environmental predictability and the two DA features. Unfortunately, they varied their choices of DA features in a predominantly dysfunctional manner.[11] The results of H2 indicated that users choose between DA features based on their

[11] The scatterplots displayed in the interfaces were probably important to the users in choosing between the DA features. The high-predictability scatterplot resembles the classic textbook example of a data set ideal for building a regression model. The low-predictability scatterplot is clearly more dispersed. This may have been a cause in participants choosing the regression aid in the former scenario, although they could have performed better with the database aid because of the missing cue (location). This interpretation is consistent with the argument of this paper because it still suggests that users (via the choice heuristic) improperly incorporate and respond to the information provided by the DA features and the DSS.

perceived competencies with the decision aids. This result suggested that users' assessment of their cognitive ability at using a DA feature competed with their (incorrect) assessment of the match between DA features and the information environment.

These results differ from "illusion of control" findings (Davis and Kotteman 1994). The illusion of control is a heuristic for choosing the alternative that provides the greatest control. Davis and Kotteman (1994) show that this heuristic can be dysfunctional in DA usage when the DA providing the most control is not the DA providing the best advice. Illusion of control does not explain our findings. The database aid provided more control than did the regression aid, but the database aid was not selected predominantly in either environment, contrary to the illusion of control. Furthermore, if control were driving the choice, one would expect users to choose the DA feature that provides the most control (database aid) for the environment in which control is most obtainable (high predictability). The opposite occurred. Users predominantly chose the passive, noncontrollable regression aid in the high-predictability environment where they had the most control over solving the problem correctly (i.e., less random error). Also, they chose the interactive, controllable database aid as often as the regression aid in the low-predictability environment where users were unlikely, due to high noise, to see patterns that would allow them to benefit from the increased control over the problem provided by the database.

As to why the heuristic takes the particular form revealed by this study (i.e., choosing the least effective DA feature more than or as often as the most effective DA feature), we offer the following speculation. Behavioral researchers have demonstrated that when confronted with a novel situation, organisms react with an orientation response in which processing is reduced and input receptivity is increased (Pavlov 1960). Conversely, in familiar situations, organisms increase processing and decrease input.[12] Accordingly, in our experiment, in the high-predictability environment, the heuristic, as an orientation response, led to predominantly choosing the process-driven DA feature (regression aid) because the lack of noise allowed familiar patterns to be evident. This enabled subjects to focus on processing over data acquisition. In the low-predictability environment, the heuristic led participants to choose the input-driven DA feature (database aid) as often as the more accurate regression aid because this noisy environment did not immediately reveal any familiar patterns. Participants wanted more data about an unclear situation.

Hypothesis 3 examined the relationship between the choice and assignment of a DA feature. Testing H3 provided partial support for the expectation that users that choose a given DA feature outperform those that have the same DA feature assigned. The results from H1 indicated that the benefit of exclusive user choice on accuracy varies (declines) when the *ceteris paribus* restrictions on H3 are removed, i.e., when chosen and assigned DA features are compared across multiple DA features. The *post hoc* analysis suggested that motivational factors partially explain the results H3. Under conditions like those in this study, gains in performance due to motivation are apparently inadequate to compensate users for choosing the less effective DA feature.

Limitations and Future Research

This study has several limitations suggestive of future research. First, the nature of exclusive user choice heuristic was incompletely defined by this study. We think that the heuristic used for choosing the DA features is a relatively new and undeveloped heuristic, or, if it is a well-established

[12] This is the same response as when a deer, for example, freezes in the headlights of an oncoming car. The animal wants to collect more data before responding. In a nontechnological environment, this would be an appropriate response to something approaching at a natural speed. When technology—the speed of the car—is introduced, the response becomes potentially fatal. It may be the same scenario, involving the introduction of technology, which makes the responses of the participants in the present experiment dysfunctional.

heuristic, its application in a technology-rich situation involves unexpected changes in its earlier behavior. Future research needs to investigate heuristics when used with advanced information technology.

The scatterplots used in the DSS to display environment predictability illustrate the above limitation. The display of various types of environmental and task information is a critical part of any DSS. Implementing a particular display in a DSS excludes all other options for the display feature. Consequently, any implementation will carry with it limitations. Scatterplots, for example, may be suggestive of regression lines because of their use of x- and y-axes. As such, they may have influenced the subjects in their choices.[13] Future research should investigate how different implementations produce different results.

A second limitation involves the DA features used in the experiment. We chose a regression aid and a database aid because they represent two of the most common types of DA features (model-driven and data-driven) and to build on prior research. Furthermore, they represent two main types of human cognition (computation and pattern matching), increasing the generalizability of the results. However, there are other types of decision aids besides these two (cf. Power 2001). Research using other DA types should expand our understanding of the impact of user choice on decision aid usage.[14]

A third limitation arises in regard to reconciling the "negative" results of H1 (i.e., users choosing the least effective DA feature) and the "positive" results of H3 (i.e., those allowed to choose between DA features marginally outperforming those assigned a specific DA feature). Our *post hoc* analysis indicated that motivational factors may play an important role in synthesizing these results.

A fourth limitation involves the exclusive choice implementation in the experiment, i.e., choice was forced so that subjects would make excluding choices. However, we do not contend that forced-choice scenarios involving IT are common in the real world, only that they can proxy for exclusive user choice behavior. Future research might investigate the occurrence of exclusive choice in an unforced manner. This could be done, for example, with an experiment that allows subjects to freely use, not use, or partially use any, some, or none of the multiple DA features provided, monitoring the subjects for occurrences of exclusive user choice.

Contributions

This research contributes to our understanding of how and why choice behavior affects the use of DSS. Prior research (Becker 1997; Dilla and Stone 1997; Jones and Schkade 1995; Whitecotton and Butler 1998) investigated exclusive user choice in relation to information acquisition, information choice, problem representation, and judgment presentation. This paper adds to that body of knowledge by examining exclusive user choice between multiple DA features in a DSS, wherein choice eliminates use of DA features not chosen. Accordingly, exclusive user choice is examined within a specific design and technology context, a context that is, nevertheless, common.

Single IT systems can contain numerous applications; e.g., the presence of multiple DA features in a DSS (Power 1997; Microsoft 2001; Turban et al. 2001). However, designing the right mix of features and applications is difficult because of the variety of users and tasks that interact with the information system. This situation leads to systems in which some features receive little or no use (Stabell 1983; Swisher 1996). Numerous studies have investigated DA under-reliance, i.e., choosing to partially use a feature. This study helps fill the gap in research on nonreliance, i.e., choosing to not

[13] It is possible that the scatterplot displays biased subjects toward choosing the regression aid over the database aid because the plots are typical of regression line illustrations found in textbooks. However, note that in terms of all 20 choices, the choice percentages of the two DA features were not significantly different (p-value = 0.211).

[14] A limitation involving the display is that the screen layout was static; e.g., the regression aid was always in the upper half of the screen, while the database aid was always in the lower half. This may have led to order effects that could not be tested.

use a feature. It shows that such choice has significant consequences for how users utilize multiple DA features. Because the impact may be negative (as in H1) or positive (as in H3), relying on user heuristics is not a sufficient basis to assure that DA features are used in the most effective manner.

The results from H1 indicated that undirected use of DSS with multiple DA features can result in suboptimal performance. This conclusion supports the type of IT design philosophy evident in Microsoft's Visual Studio for Application (VSA) (Microsoft 2001), i.e., customizing the system as closely as possible to the needs and capabilities of the user and assist the user in assessing the fit between task and application. However, the results from H3 suggested that this design approach may not always be the best one because it shows that there are conditions in which exclusive user choice can be beneficial. For example, if management can ascertain *a priori* user preferences for DA types (via such tests as the GEFT, MCT and MBTI; see Wheeler 2001), then it may be possible to place users in situations in which they will choose the DA type most appropriate for the task. Accordingly, organizational studies of user choice and DA usage are needed to address these issues from a management perspective.

The results also suggest that enabling exclusive user choice in a DSS may degrade judgment quality if one DA type is clearly superior to another because there appears to be a common bias toward choosing the least effective decision aid for the task more than or as often as the most effective DA feature. Under such circumstances, designers and managers may want to limit user choice by increasing design restrictiveness and directedness (Silver 1988, 1990). On the other hand, if the alternative decision aids are equally effective, the effect of exclusive user choice should improve judgment quality. In that case, allowing users to choose should be encouraged because, for a given decision aid, those who choose a tool outperform those required to use the same tool, probably due to motivational factors.

This study provides important indications about the heuristic used to choose between DA features. While other decision-making heuristics can have a detrimental effect on performance under certain restricted circumstances, our experiment raises the specter of a heuristic (exclusive user choice) being *predominantly* dysfunctional. It may, for example, be a new heuristic designed to deal specifically with the use of IT and thus has had too short a history to be fully tested. The choice heuristic may be a faultily developed choice method that has not yet been selected out of human cognition through trial and error. Alternatively, the choice heuristic may not be a new heuristic, but instead it may be an established heuristic applied to new situations for which it is not suitable. Either explanation opens up many interesting research questions about heuristics and biases when applied to technology. How do heuristics, developed for one set of conditions (e.g., non-IT or unaided decision making), transfer to and perform in other conditions (IT-rich or decision-aided)? Are there heuristics presently existing or currently developing for decision aid or IT use? Can we, as researchers, assist this process?

REFERENCES

Arkes, H. R., R. M. Dawes, and C. Christensen. 1986. Factors influencing the use of a decision rule in a probabilistic task. *Organizational Behavior and Human Decision Processes* 37: 93–110.

Arnold, V., and S. G. Sutton. 1998. The theory of technology dominance: Understanding the impact of intelligent decision aids on decision makers' judgments. *Advances in Accounting Behavioral Research* 1: 175–194.

Ashton, R. H. 1982. *Human Information Processing in Accounting*. Sarasota, FL: American Accounting Association.

———. 1990. Pressure and performance in accounting decision settings: Paradoxical effects of incentives, feedback, and justification. *Journal of Accounting Research* 28: 148–180.

Baron, J. 1994. *Thinking and Deciding.* Second edition. New York, NY: Cambridge University Press.

Becker, D. A. 1997. The effects of choice on auditors' intrinsic motivation and performance. *Behavioral Research in Accounting* 9: 1–19.

Brown, D., and D. R. Jones. 1998. Factors that influence reliance on decision aids: A model and an experiment. *Journal of Information Systems* 12: 75–94.

Buss, D. 1998. *Evolutionary Psychology: The New Science of the Mind.* Boston, MA: Allyn and Bacon.

Davis, F. D., and J. E. Kotteman. 1994. User perceptions of decision support effectiveness: Two production planning experiments. *Decision Science* 25: 57–78.

Dietrich, J. R., and R. S. Kaplan. 1982. Empirical analysis of the commercial loan classification decision. *The Accounting Review* 62 (1): 18–38.

Dilla, W. N., and D. N. Stone. 1997. Response scales in risk judgments: The effects of representation, fineness, and user choice. *Journal of Information Systems* 11: 75–96.

Dix, A., J. Finlay, G. Abowd, and R. Beale. 1993. *Human-Computer Interaction.* New York, NY: Prentice Hall.

Dos Santos, B. L., and M. L. Bariff. 1988. A study of user interface aids for model-oriented decision support systems. *Management Science* 34: 461–468.

Fodor, J. A. 1983. *The Modularity of Mind.* Cambridge, MA: MIT Press.

Hoch, S. J., and D. A. Schkade. 1996. A psychological approach to decision support systems. *Management Science* 42: 51–64.

Huber, G. P. 1983. Cognitive style as a basis for MIS and DSS designs: Much ado about nothing? *Management Science* 29: 567–579.

Jones, D. R., and D. A. Schkade. 1995. Choosing and translating between problem representations. *Organizational Behavior and Human Decision Processes* 61: 214–223.

———, D. Brown, and P. Wheeler. 2001. Justification in the presence of a decision aid: Effects on consistency and performance. *Advances in Accounting Behavioral Research* 4: 187–206.

Kahneman, D., P. Slovic, and A. Tversky, eds. 1982. *Judgment Under Uncertainty: Heuristics and Biases.* New York, NY: Cambridge University Press.

Libby, R. 1981. *Accounting and Human Information Processing: Theory and Applications.* Englewood Cliffs, NJ: Prentice Hall.

Marais, M. L., J. M. Patell, and M. A. Wolfson. 1984. The experimental design of classification models: An application of recursive partitioning and bootstrapping to commercial bank loan classifications. *Journal of Accounting Research* 22 (Supplement): 87–114.

Microsoft. 2001. VSA brings programmability to .net applications: Customize your apps for the Internet. Sponsored white paper *.net Magazine* November 1–8. Available at: http://www.fawcette.com/dotnetmag/whitepapers/microsoft/Microsoft_wp.pdf.

Pavlov, I. 1960. *Conditioned Reflexes: An Investigation of the Physiological Activity of the Cerebral Cortex.* Translated and edited by G. V. Anrep. New York, NY: Dover Publications, Inc.

Peterson, D. K., and G. F. Pitz. 1986. Effect of input from a clinical model on judgment. *Journal of Applied Psychology* 71: 163–167.

Power, D. J. 1997. What is a DSS? *DS*Star, The On-line Executive Journal for Data-Intensive Decision Support* 1 (3, October 21): 1–4. Available at: http://dssresources.com/papers/whatisadss/index.html.

———. 2001. Supporting decision makers: An expanded framework. *Informing Science* June: 1–6.

Rathjens, D., and H. Vanderberg. 1998. *Mineset™ User's Guide.* Mountain View, CA: Silicon Graphics, Inc.

Silver, M. S. 1988. User perceptions of decision support systems: An experiment. *Journal of Management Information Systems* 5: 51–64.

———. 1990. Decision support systems: Directed and nondirected change. *Information Systems Research* 1: 47–70.

Sprague, R. H., and E. D. Carlson. 1982. *Building Effective Decision Support Systems.* Englewood Cliffs, NJ: Prentice Hall.

Stabell, C. B. 1983. A decision-oriented approach to building DSS. In *Building Decision Support Systems*, edited by J. L. Bennett, 221–260. Reading, MA: Addison-Wesley Publishing Company.

Swisher, L. 1996. *Report on Medicaid Decision Support Systems (DSS).* Baltimore, MD: Medicaid Bureau, Office of Information Systems and Data Analysis.

Turban, E., E. McLean, and J. Wetherbe. 2001. *Information Technology for Management.* Second edition. New York, NY: John Wiley & Sons, Inc.

Tversky, A., and D. Kahneman. 1974. Judgment and uncertainty: Heuristics and biases. *Science* 185: 1124–1131.

Vessey, I. 1991. Cognitive fit: A theory-based analysis of graphs vs. tables literature. *Decision Science* 22: 219–241.

———, and D. Galletta 1991. Cognitive fit: An empirical study of information acquisition. *Information Systems Research* 2: 63–84.

Wheeler, P. R. 2001. The Myers-Briggs Type Indicator and applications to accounting education and research. *Issues in Accounting Education* 16 (1): 125–150.

Whitecotton, S., and S. Butler. 1998. Influencing decision aid reliance through involvement in information choice. *Behavioral Research in Accounting* 10 (Supplement): 182–200.