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Effectiveness of decision support systems: development or reliance effect?

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Abstract

Despite the large number of empirical investigations of DSS on decision outcomes, very few studies have incorporated longitudinal designs to assess DSS effectiveness. This study proposes that effects of DSS on decision outcomes develop over time. The study evaluated whether improvements in decision quality typically associated with DSS were due primarily to 'development' or 'reliance' effects. Using an add-on and take-away design, we examined whether introduction of DSS contributes to decision quality after controlling for task familiarity. We also evaluated decision-makers' performance after removing the DSS. Results indicated that although DSS contributed to decision quality after controlling for task familiarity, increased decision performance of DSS-aided decision makers may be due to reliance rather than better conceptual understanding of the decision problem. Implications of these results for design and implementation of DSS are discussed.

Keywords: Group DSS; DSS effectiveness

1. Introduction

Interest in use of decision support systems (DSS) to improve the quality of decision-making in organizations has increased dramatically in the last ten to fifteen years. Applications of DSS have been developed in such areas as strategy formulation and corporate planning [1,2], product marketing [3,4], production and inventory scheduling [5,6], tax and auditing [7–9], portfolio management [10–12] and many others. Using in-person interviews, Hogue and Watson [13] documented the field use of DSS by a number of firms in decisions involving pricing and route selection, corporate planning and forecasting, investment evaluation, pricing advertising and promotion, evaluation of drilling sites, train dispatching, and evaluation of warehousing and retail store locations. Parallel to this increased interest in DSS applications, the number of conceptual and empirical investigations examining effects of DSS on decision outcomes has also risen substantially in recent years [14].

Despite this rapid increase in the popularity of DSS, significant questions regarding their use remain unanswered. While numerous studies have documented improvements in quality of decision outcomes through introduction and use of DSS, virtually no empirical research has examined *why* use of DSS results in higher quality decisions. This is important in the design and construction of any systems that

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assist decision makers or model experts in semi-structured or ill-structured decision situations. To accurately portray and capture experts' decisions, it is critical to understand the ways that DSS may affect decision making processes, decision makers' decision actions and subsequent outcomes.

As an initial effort in this area, we examined the viability of two competing explanations of DSS effectiveness. One widely proposed and accepted rationale for the development and use of DSS is that DSS's major value is in removing information overload and redundancy by summarizing, categorizing, and projecting important data, thus decreasing the cognitive effort required to process large amounts of information and allowing decision makers to focus on more central elements and issues in the decision process. This has been hypothesized to lead to such benefits as examination of more alternatives, stimulation of new approaches to problem solving, improved communication, decreased time spent in processing information, increased confidence in the decision and ultimately higher quality decisions by letting decision makers focus on strategic issues. We refer to this potential explanation of DSS effectiveness as a 'development effect.' The use of DSS may assist decision makers in developing a greater conceptual understanding of relationships between parameters of a decision problem, such as task environment, forecasts, decision actions and competitor responses. For example, the use of 'what-if' or Monte Carlo analyses, common in many DSS, allows the decision maker to evaluate numerous courses of action and to develop an increased understanding of how decision factors affect other input and outcome variables. If such a development effect occurs, it may be expected that this understanding could facilitate future decisions of the same type and possibly be transferred to other decision situations.

Conversely, particularly in cases where the DSS was built by somebody other then the decision maker, it is possible that DSS-aided decision makers may assume the passive role of information supplier to the DSS and may not attempt to understand interdependencies or underlying relationships in the decision task. Any increase in decision quality under these circumstances may primarily be due to factors such as decreases in computational errors or inclusion of additional relevant variables, rather than increased understanding of the decision problem or its underlying relationships. If this occurs, the function of the DSS may move from a decision *support* system to a decision *making* system. We refer to improvements in decision quality under these circumstances to as a 'reliance effect.' Decision makers may become overly dependent on the DSS and not attempt to understand or learn relationships between factors affecting the decision. This suggests that use of DSS could actually decrease decision makers' effectiveness in future decisions as decision makers may defer to the DSS to make the decision for them.

Another issue of concern in DSS research that must be addressed in evaluating potential development and reliance effects is the distinction between task familiarity effects and DSS effects on decision quality. Many previous DSS studies have used case study methods and post test only designs. As noted by Sharda et al. [15], longitudinal studies can more accurately portray effectiveness of DSS. For example, a typically employed experimental design in DSS research has decision makers make a decision without DSS and then the same decision (or type of decision) with DSS. Improvements in decision quality are attributed to DSS when task familiarity is a strong rival plausible explanation. Numerous studies in other decision making areas have found that simple task repetition can improve performance. A more accurate assessment of DSS effects on decision quality would incorporate a design where decision makers were already familiar with the decision task.

Thus, this paper reports results of an experiment designed to address these two issues. Our major purpose was to assess whether improvements in decision performance resulting from use of DSS are primarily due to development or reliance effects. In addition, we evaluated these effects of DSS on decision quality after controlling for task familiarity.

2. Previous research

In this section we summarize previous DDS investigations relevant to this study. Early empirical efforts in the design and construction of management information systems (MIS) have been instrumental in the development of DSS. Studies in this area have been reviewed previously by Dickson et al. [16], Courtney, et al. [17], and Jarvenpaa et al. [18] and are not summarized here. In our review of empirical DSS research we focused primarily on field tests and laboratory studies as these methods emphasize greater experimental control and therefore provide stronger inferences than do case studies and field studies.

More recent reviews of empirical DSS literature have been conducted by Elam et al. [19], Aldag and Power [20] and Benbasat and Nault [21]. The majority of empirical investigations of DSS can be broadly classified into two categories. The first group of studies have evaluated the relative performance of DSS-aided decision makers versus counterparts operating without DSS. Examples include Benbasat and Schroeder [5], Benbasat and Dexter [6], Eckel [3] and Aldag and Power [20]. In a recent review of such studies examining availability of DSS, Sharda et al. [15] concluded that although results of previous works were mixed, laboratory studies employing 'objective' measures of decision performance and using repeated measures designs did indicate that DSS availability could be expected to increase decision quality. Thus, the question of reliance or development effects examined in this study are predicated on the belief that use of DSS does increase decision quality. As noted earlier, however, it is unclear whether this increased quality is due primarily to reliance of decision makers on the DSS to make the decision, thereby decreasing computational errors (reliance effect) or improved conceptualization and understanding of the decision problem (development effect).

The second major stream of inquiry in DSS research has focused on characteristics or parameters in the design of DSS that should result in higher levels of decision quality and/or user attitudes. Examples of variables investigated in these lines of inquiry include format, content and/or media used in presenting information [16] and interactiveness of the decision support system [14]. An outgrowth of these studies is the design of support systems to accommodate differences in cognitive style among decision makers [22,23].

Partly as a result of the focusing of previous research efforts on issues involving effectiveness and optimum parameters of DSS, there appears to be a paucity of theory development and empirical research examining *why* DSS does increase decision making performance. Benbasat and Nault [21] noted that relationships between DSS and decision performance remain largely driven by ad hoc selections of variables with little consideration of understanding how DSS affects decision outcomes. Thus, our objective was to examine the viability of competing 'development' and 'reliance' explanations underlying the frequently noted findings of increased decision effectiveness for DSS users.

To more accurately separate DSS effects from potential task familiarity effects and to assess the possible presence of reliance or development effects among DSS users, a number of methodological issues in previous empirical DSS studies were addressed and incorporated into the experimental design. Sharda et al. [15], in a recent review of studies examining DSS effectiveness, identified five methodological problems to be considered in DSS research. These include emphasis on cross sectional, one time measures of decision outcomes; the 'black box' nature of most DSS; use of subjective ratings of decision outcomes and quality; reliance on individual versus group unit of analysis and use of relatively weak experimental designs in inferring causes of decision outcomes.

Similar concerns about the design and use of experiments to evaluate effects of DSS have been raised by Gardner et al. [10] who addressed subject incentives and the value of controlled laboratory experimentation.

This study attempted to address the frequently reported methodological problems raised above. First, the experimental design used equivalent decision making teams in a repeated measures 'take-away' and 'add-on' design where some groups had DSS removed during the experiment while other groups had DSS added later to help in decision tasks. Control groups were not allowed to use DSS, while another set of groups had full access to DSS during the duration of the experiment. This allowed separation of DSS effects from task familiarity or repetition effects, thus permitting more accurate tests for reliance and development effects. The need for designs of this type in DSS investigation has been raised previously by McIntyre [24], but they have not been widely used. This design is more fully described in the method section. Second, the DSS used was built using Interactive Financial Planning System (IFPS), a commercially available DSS generator that allowed 'what-if' and 'goal-setting' analyses as well as Monte Carlo simulation. The decision task involved semistructured decisions consisting of production volumes, design, pricing and promotion strategies, plant size and investment of earnings. Third, decision quality measures were objective or 'hard' measures, including net earnings, return on investment, return on assets, market share, etc. Fourth, management teams were used as decision making groups for this study. Discussions with decision makers at a number of firms revealed that most organization level decisions (like those made in the current study) are a product of a group decision process. DeSanctis and Gallupe [25] have identified three levels of group decision support systems (GDSS). The DSS used in this study is a level 2 GDSS, representing budgeting/forecasting models. Intact teams with prior experience together were used as opposed to creating groups only for the study. Fifth, these management teams were provided instruction and access to the DSS, but DSS use was at the teams' discretion. Teams were encouraged, but not required, to use DSS. Many earlier studies have required that the DSS be used. Whether one uses DSS is a decision usually left to the manager or decision maker. A DSS builder-analyst rarely has the authority of force use of a DSS as may be done in a lab or class setting. Thus, we were able to evaluate effects of availability of DSS and DSS usage.

3. Hypotheses

The central purpose of the study was to examine *why* DSS aided decision makers outperform non-DSS decision makers. As a precursor to evaluating possible development and reliance effects, we first investigated the generally held belief that use of DSS would result in higher levels of decision making performance. This hypothesis is based on results of a number of previous studies noting increased levels of decision performance for DSS users [26–30,24,3,31,15].

As noted earlier, we sought to examine the viability of two potential explanations for improved decision performance for DSS users. Thus, we first tested to see if DSS aided decision makers did perform better than non DSS aided decision makers. In testing DSS effectiveness we felt that it was important to distinguish between DSS availability and actual DSS usage. Thus, we developed two sub hypotheses to test DSS effectiveness. Hypothesis 1A proposed a main effect of DSS availability on decision performance. It is this hypothesis that has been examined in most prior DSS studies.

Hypothesis 1A: Groups with access to DSS will have higher decision performance than groups without access to DSS.

We also developed a hypothesis regarding extent of actual DSS usage and decision performance for those groups with access to DSS.

Hypothesis 1B: Level of DSS usage is positively related to decision performance.

Previous studies generally have inadvertently inferred a direct relationship between extent or degree of DSS usage and decision quality. Most studies, however, have not distinguished between availability and usage of the DSS. This is partly because usage may be hard to measure. It is possible that some researchers may have required a certain level of use of the DSS. However, this is usually not reported. Hypothesis 1B allowed us to more clearly examine the relationship between DSS usage and decision performance for DSS aided groups.

The second hypothesis evaluated the presence of reliance and development effects. Because the current state of theory development in this area does not suggest which of these phenomena would be more likely to occur, we separated this hypothesis into two competing explanations, both consistent with increased decision quality performance by DSS users. For each of these hypotheses, we evaluated the presence of development or reliance effects after controlling for task familiarity. Hypothesis 2A proposes a development effect.

Hypothesis 2A: Performance of DSS groups will not decrease when the DSS is removed.

As noted earlier, both development and reliance effects are consistent with the frequently noted results of improved decision quality through implementation of DSS. If the development effect is a viable explanation, removal of DSS from decision groups already familiar with the decision task and environment should not have an adverse effect on decision performance. Decision makers would already have learned the nature of interrelationships between decision factors and have an increased conceptual understanding of the decision. Loss of the DSS would, therefore, should not significantly decrease decision makers' conceptual understanding and subsequent decision performance. In addition, these decision groups should continue to perform better than decision groups without DSS during the decision process.

The alternative hypothesis posits a reliance effect.

Hypothesis 2B: Performance of DSS groups will decrease when the DSS is removed.

A number of authors have suggested drawbacks to the use of DSS in decision making. Chamot [32] suggested that implementations of DSS or expert systems (ES) may alter job functions, resulting in 'deskilling.' This occurs when the role of the decision maker changes from one of understanding and conceptual mapping of the problem to simply accessing and manipulating information. Similarly, Baab [33] noted in an auditing framework that increased auditing judgment quality is a function of establishing and maintaining thought processes rather than repetitively accepting a DSS-supplied answer. If DSS fosters a heavy reliance by decision makers on the DSS, resulting in decreased conceptual understanding of the decision, then removal of the DSS should negatively affect subsequent decision quality. Again, the magnitude of this effect could be examined by comparing these decision groups to those without DSS and to decision groups with access to DSS.

4. Method

4.1. Subjects

Participants were senior students enrolled in eleven sections of a capstone business policy/strategy course at a midwestern university. All students in all sections of the course participated in this study. In this course, students interact in 3–4 person groups on a number of projects such as industry analyses and company strategy development. These groups are formed at the beginning of the semester and members remain in the same group. Groups are formed so that each group is similar with respect to student G.P.A., major, quantitative ability and computer familiarity. No differences in course grade was noted for groups across the experimental and control conditions. These existing groups were used as the decision making 'management teams' for this study.

Each team was responsible for all decisions, operations, and resulting performance of an organization in a computer assisted game modelling a business industry environment. All participants were told that fifteen percent of their final course grade would be determined by their management team's performance. Thus, a strong motivation was present for teams to do their best in the simulation game.

4.2. Task

Each course section was a distinct industry environment comprised of eight separate organizations. Thus, there were eleven industries consisting of eight teams each. Subjects participated in a nine week simulation that models a competitive industry. The firms supply a number of products of varying quality and price to differing market segments. The particular simulation used in this study was the Executive Game [34].

This game required each management team to make weekly product decisions including sales price, advertising/marketing budget, design/quality budget, and production quantity for three different product lines. In addition, plant capacity and investment decisions were required. In total, 17 decisions were required from each team. The teams were informed that these 17 decisions represented a collective three month (quarterly) plan. Team decisions were due at the end of each week.

Each of the three product lines was generically defined to minimize possible familiarity effects by participants. Teams were told that total industry and individual firms' product demand was a function of general economic conditions as well as the actions of the other teams within their industry. Each team was told that they were competing only with the other seven teams in their industry (course section). All teams were equally affected by general economic conditions, seasonal demand variations and consumer reactions within the game and also by decisions of the other firms. Teams were told that their objective was to maximize long-term earnings of their firm.

4.3. Procedures

Each of the eleven course sections was assigned to an experimental or control condition. Three experimental conditions and a control condition were created. These are summarized in Fig. 1. Each team was informed that the first week's decision would be considered as a practice decision and would not be used in evaluating performance. This allowed participants to become familiar with the game procedures prior to the start of the experiment. Thus, even though the students played the game for 10 periods, only nine of these (2–10) were used for analysis.

In the 'always' condition, teams were provided with DSS for all nine decisions. In the 'take-away' condition, teams were provided with DSS for the first five weekly decisions. They were not told that the DSS would be removed during the semester. After the fifth decision, the DSS was removed for the last four decision periods. In the 'add-on' condition, teams made decisions during the first four periods without DSS. They were not told that DSS would be available later. After the fourth quarter's decisions were made, the DSS was introduced and made available for the last five periods. The type of DSS available was identical in all three experimental conditions and is explained in a later section. Control groups made decisions without DSS.

Four weeks after the start of classes, the decision game was introduced in all course sections. This allowed course instructors to have already formed groups for the other projects required in the course. Thus the teams had worked together on other assignments prior to the start of this study. Specific details regarding the Executive Game were explained by the instructor. Each team was provided with a 20 page manual containing information on the game, sample decision sheets, etc. The teams kept this manual for reference during the game. Teams within each industry (course section) were informed that they would be competing with each other. There were no 'dummy teams' in the game. The content of the introduction and explanation of the game was the same in all course sections even though instructors differed across the course sections. Five instructors taught the eleven sections used in this study.

Teams used supplied decision sheets to record the required 17 decisions each period. Decisions were due each Friday and results of each quarter's decisions were distributed in separate envelopes to each team on the following Monday. Each team had five days to review results and formulate the next quarter's decision. The game parameters were the same for control and experimental groups.

The nature of the feedback given to the teams was identical in all course sections. Information particular to each team was provided, including total

EXPERIMENTAL CONDITION	PRACTICE SESSION									
Always	0	X	X	X	X	X	X	X	X	X
Take-Away	0	X	X	X	X	X	O	O	O	O
Add-On	0	O	O	O	O	X	X	X	X	None*
Control	0	O	O	O	O	O	O	O	O	O
	1	2	3	4	5	6	7	8	9	10

PERIOD

X = DSS AVAILABLE FOR USE
O = NO DSS AVAILABLE

Fig. 1.

profits/losses, net earnings, cash flow, financial status and plant capacity. Detailed information on each of the three product lines was included. In addition, each team received aggregate industry information and projections including business forecasts, market indexes, total market demand, etc.

4.4. Measures

4.4.1. Independent variable

The decision support system used in this study, Exec-DSS, was created using Interactive Financial Planning System (IFPS) developed by Execucom [30]. IFPS is a readily available software package that is representative of DSS generators. Models developed using IFPS are usually close to statements of the problems since it accepts descriptive variable names of any length. A number of features of IFPS enhance users' ability to easily change parameters of the model. One such feature is a 'what if' option allowing users to change basic model parameters or relationships between variables and examine the effect of these changes on performance variables. A second 'goal seeking' option permits users to determine levels of input variables needed to achieve particular outcome levels. An example of this would be break even analysis. A Monte Carlo simulation option permits users to examine probability distributions of decision performance variables given user-supplied probability distributions of uncertain input variables.

These features allowed the management teams to readily examine effects of changes in such areas as industry forecasts, pricing/production and other firms' anticipated strategies. The version used in this study was for mainframe computer, but microcomputer use is also possible. We used this particular DSS because of its representativeness of current DSS generators, user friendliness and flexibility in allowing management teams to explore any option that they desired. Exec-DSS is a form of financial analyses model. Decision teams entered values of inputs such as pricing, budget, plant capacity, inventory, etc. The DSS then generated reports of effects of these input levels on performance outcomes. Any number of changes could be examined through the what if, goal seeking and Monte Carlo options. The management teams were not restricted in their access to the DSS. Each team was issued an account number and password and could use the DSS from any of the numerous mainframe terminals on campus. There was no time limit on DSS usage. The type and amount of information available through the DSS was the same for all DSS-aided experimental groups. The DSS was introduced by the second author to each experimental course section. Basic use of IFPS was explained, followed by a review of Exec-DSS. Specific examples of the options were included and any questions were answered. Groups in the always and take-away experimental conditions received DSS instruction in conjunction with the start of the Executive Game. Experimental groups in the add-on condition were given access to the DSS after performance feedback from the fourth period's decision was distributed. Thus, the 'always' groups used DSS for the full nine week study. 'Take-away' groups were provided DSS for the first five weeks only and 'add-on' groups had DSS available for the last five weeks only. During the study, graduate assistants familiar with the Executive Game and the DSS were available approximately six hours per week. These assistants answered operational questions about the game or the DSS but did not provide interpretation of results or assist in formulating team decisions.

Control group course sections received a full explanation of the Executive Game but no instruction in DSS use. It had been announced earlier that IFPS would be covered in only some course sections due to limited resources. Control groups were told that their teams' performance would be evaluated only against the other teams in their industry/course section.

The decision process for all experimental and control groups involved examination of historical data, results of the prior quarters decisions and forecasts. Alternatives were developed and analyzed by teams to arrive at a decision strategy each period. The experimental groups could use Exec-DSS to assist in formulating their strategy. The non-DSS (control) groups were allowed to use calculators or other tools. The DSS did not contain any additional information not available to the control groups.

4.4.2. Dependent variables

Prior empirical DSS studies have used a variety of outcome or performance measures. The management teams' performance feedback generated by the Executive Game contained numerous decision performance data. Examples included market share, gross sales, net earnings, net assets, return on investment, etc. As expected, significant multicollinearity was evident among these variables. At the introduction of the game, participants were informed that net earnings would be the primary factor used in evaluating team performance as it represented a 'bottom line' measure of decision effectiveness. Therefore, this variable was used as the primary measure of decision quality. Similar patterns of results were obtained using other decision performance measures.

Computer records were also maintained for each team's DSS usage. This allowed us to determine the extent and nature of on-line DSS usage by teams for each quarter's decisions and permitted us to evaluate any differences between decision groups with access DSS compared to the extent of DSS usage by the groups.

5. Results

Because the number of potential pairwise comparisons over the nine experimental periods was large, only pre-planned comparisons were conducted to control for inflated alpha (Type I) error. A summary of results of experimental and control conditions for each period is presented in Table 1. [1] Fig. 2 displays these results graphically, showing the percent difference in average group earnings under the experimental conditions compared to control (no DSS) teams. For example, in period 4, take away and always sections showed approximately 28% higher earnings than the control groups, whereas add-on teams realized about 5% lower performance than the control teams. This figure allows us to visually examine the effect of each experimental condition after controlling for variation due to economic cycles, which were experienced by all teams in each experimental condition equally.

Hypothesis 1A proposed that groups with access to DSS would perform better than non-DSS groups. Repeated measures analysis of variance (ANOVA) was used to compare the always and control groups for the nine week period. Results indicate no significant difference over the combination of the nine periods. DSS-aided always groups did, however, outperform non-DSS groups in seven of the nine periods. Using the Wilcoxon signed-rank test statistic, DSS-aided groups performed better ($p < 0.05$). Thus, mixed evidence was obtained.

Hypothesis 1B posited a main effect of DSS usage on decision performance. As noted earlier, we felt that it was important to separate DSS usage from DSS availability effects. Since Exec-DSS was accessible via any of the mainframe terminals, computer records of connect time were evaluated for decision groups in the always experimental condition. [2] As expected, significant variance in DSS usage was evident between these teams. To assess the effects of DSS usage, for each period we divided always groups into high and low DSS users, based on each period's median connect time for those groups that used the DSS for that period's decisions. We also created a comparison of groups that had access to DSS, but did not use DSS for that period's decision. We then evaluated net earnings each period for high DSS use, low DSS use, no DSS use but available and control (no DSS) groups. Results are summarized in Table 2. As reflected in Table 2, initial use of the DSS was heavy in periods 2 and 3. However, in periods five through nine comparisons of the groups are based on small samples. Because of these smaller sample sizes in later periods, ANOVA analyses were not conducted because of the increased chance of Type II error.

Implications of this pattern of usage are discussed in the Conclusions section. High DSS use groups showed greater net earnings than low DSS use groups in six of the nine quarters. Similarly, high DSS use groups outperformed groups not using DSS in six of

[1] Because multiple instructors participated in this study, we effect coded for instructor. No instructor main effects or instructor-period interaction effects were found. As expected, a significant period main effect was noted since the nine periods include economic cycles.

[2] We did not use groups in the add-on or take-away conditions for this analysis since these groups did not have access to DSS during each of the nine experimental periods. Review of session logs indicated that groups did use DSS when connected as opposed to simply 'logging on' and conducting no analyses.

Table 1
Average net earnings of teams in each group

Experimental condition	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
Always (24)	Practice session	161 361	233 327	229 611	71 113	183 534	284 323	218 132	33 761	132 216
Take-away (24)		174 595	263 905	230 546	85 659	198 211	260 448	190 270	28 091	137 494
Add-on (24)		188 427	262 860	175 041	71 390	194 591	333 115	218 228	55 381	None[a]
Control (16)		174 936	220 119	178 266	46 169	166 052	276 217	191 452	25 829	151 448

[a]Groups in 'add-on' course sections did not submit decisions for period 10.
() = number of teams in each condition.

eight comparisons. Finally, high use groups had greater net earnings than control (non-DSS) groups in seven of the nine quarters. In total, these patterns of results suggests that DSS availability and DSS usage was positively related to decision quality.

Hypotheses 2A and 2B examined the viability of development and reliance effects, respectively. To evaluate their potential effects of DSS on decision quality after controlling for task familiarity, we examined the performance of add-on groups *after* the DSS was introduced by comparing them to control and always groups. This allowed for a clearer separation of task familiarity and DSS effects for teams in the add-on condition. These results are graphically displayed in Fig. 2. Performance of add-on groups relative to control and always groups increased after introduction of DSS for period 6 decisions. Add-on groups had higher performance than always and control groups in each of the period 6 through 9 comparisons. The net earnings were significantly greater ($p < 0.05$) in periods 7 and 9.

Similar to the previous analyses, we also examined usage patterns of the add-on groups. Again, continued use of DSS was relatively light. Of the 24

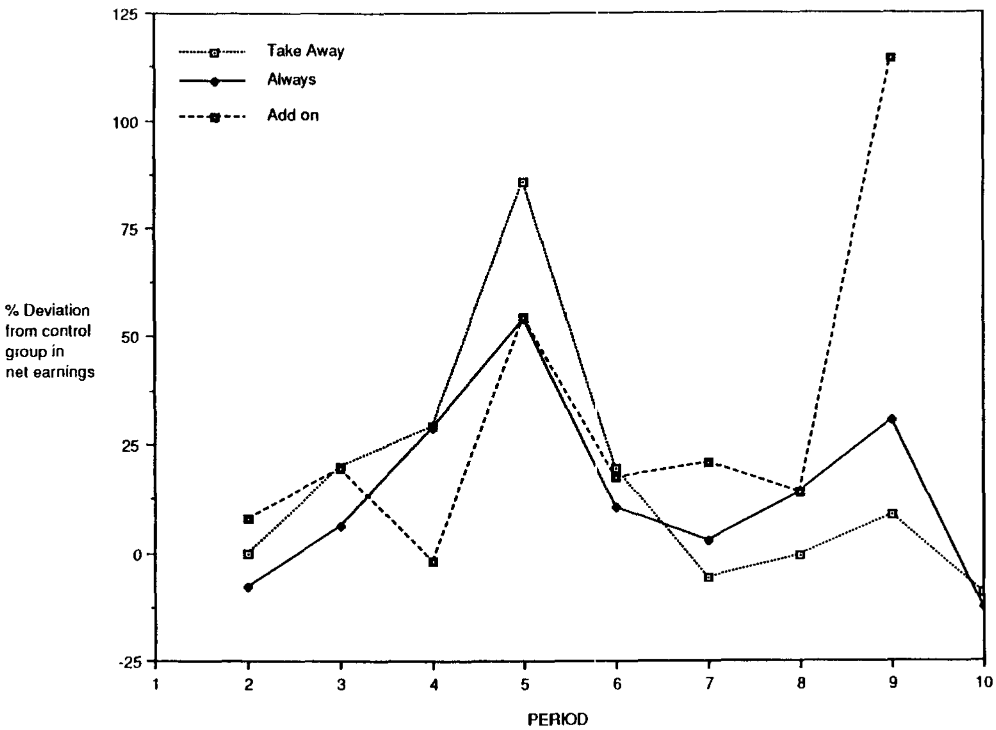

Fig. 2.

Table 2
Net earnings for high user, low user, no use and non DSS groups

	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
High DSS use	158 328 (12)	264 528 (8)	211 732 (5)	91 150 (4)	239 419 (4)	210 859 (4)	219 737 (3)	51 356 (2)	153 738 (2)
Low DSS use	164 393 (12)	187 906 (8)	246 528 (5)	65 478 (4)	148 243 (4)	211 476 (4)	195 995 (3)	22 840 (2)	43 936 (2)
No DSS use but available	None[a]	240 908 (8)	228 738 (14)	68 902 (16)	184 233 (16)	294 805 (16)	219 033 (18)	31 081 (20)	132 972 (20)
Control (no DSS)	174 936 (16)	220 119 (16)	178 266 (16)	46 169 (16)	166 052 (16)	276 217 (16)	191 452 (16)	25 829 (16)	151 448 (16)

() = number of teams in category.
[a]All teams with access to DSS did use the DSS in period 2.

add-on teams, only 11 used the DSS initially in period 6. The number of teams using DSS in periods 7 through 9 was 9, 8, and 8, respectively. Because of lower sample sizes and resultant statistical power, we did not conduct formal tests to examine the relationship between DSS usage and net earnings of the add-on groups. However, high DSS groups did generally have greater net earnings than low use and no use teams. Overall, these results provide support for the presence of development effects.

To test for possible reliance effects, we evaluated changes in performance of the take-away groups *after* the DSS was removed in period 7 decisions by comparing them to both the 'always' and control groups. Again, results are graphically presented in Fig. 2. After removal of the DSS, net earnings of take-away groups decreased relative to the always and control groups. Control groups, who never had access to DSS, had higher net earnings than take-away groups in periods 7, 8 and 10, although none of these differences were statistically significant. Similarly, always groups had higher net earnings than take-away groups in periods 7, 8 and 9. Only in period 8, however, was this difference significant ($p < 0.10$). Again, lack of statistical significance may be largely due to lower sample sizes in the later periods.

6. Conclusions

Advocates of DSS propose that these systems improve decision performance quality. We evaluated two potential explanations for such improved decision performance. The reliance effect suggests that the use of DSS may lead to deferring the decision process to 'let the computer do it'. The development effect suggests that the DSS assists the decision makers in understanding complex relationships between decision factors. Clearly, long run decision effectiveness in organizations is improved primarily by the latter. We found evidence of both effects, suggesting that while DSS did increase decision performance, this increase was due primarily to the efficiency of the DSS compared to the decision makers and not because of an increased understanding of the relationships between the decision factors by DSS aided decision makers.

6.1. Interpretation of results

Patterns of decision performance in the take-away and add-on decision groups are particularly interesting. Evidence of a reliance effect was noted among take-away groups. On removal of the DSS, performance of these groups decreased to levels lower than those of the control (non-DSS) groups. Similar to any planned change, an initial decrease in performance could be expected as a reaction to the introduction of change. However, performance of these groups did not return to their previous levels. Only in period 9 did performance of take-away groups equal control groups, who had no access to DSS during the study. Consistent with this pattern, decision performance of take-away groups after removal of the DSS was generally lower than the always groups, who were able to use DSS for the full study. Thus, evidence of a DSS reliance effect is present. It appears that DSS was not effective in improving conceptual decision-making skills for this decision task. Similar results have been noted in the use of expert systems by Murphy [35], who concluded that use of an expert system may foster high levels of dependency on the system by the decision maker that may lead to a subsequent decrease in decision effectiveness.

With respect to the presence of development effects, it is interesting to note the performance increase of add-on groups relative to always and control groups. Following introduction of the DSS, add-on groups had higher net earnings than both the always and control groups for each period. Thus, it appears that the DSS contributed to decision performance after consideration of task familiarity effects. Taken in conjunction with evidence of reliance effect, however, the DSS may have been a mechanical rather than conceptual decision aid.

Analysis of level of DSS usage revealed that while most teams did use DSS for two or three decision periods, few groups continued using DSS for the full nine week study. We did not mandate use of DSS by the decision-making teams; use was optional. We felt that this would be more representative of actual DSS use in organizations, where DSS is generally available but not required to be used. While other studies may have required subjects to use DSS, we felt that this would confound the results and seriously affect generalizability. The objective of obtaining statistically significant results from a study should not supersede the overall objective of learning more about the use of DSS. Clearly, availability of DSS can not continue to be considered synonymous with DSS usage.

A number of reasons may account for the relatively light continued use of DSS. The DSS was introduced as a 'tool' to aid the groups in making decisions. Participants were told that usage was totally up to each team. While requiring the teams to use DSS would have increased usage, we felt that this would not be representative of the design and introduction of DSS in organizations. It is also possible that many of the teams (perhaps inaccurately) felt that they understood relationships between decision factors after using DSS only once or twice. Our attempt to measure and report on DSS usage does point to a need for clearer conceptual and operational distinctions between availability and use of a DSS. Connect time is only a surrogate measure. It is possible to run large number of analyses quickly if these have been preplanned. Alternatively, a team can be lost in the use of computer, resulting in high connect time but little application of the DSS to the decision problem. We did keep session logs for each team, and verified that the teams were editing the model, running 'what-if' analyses, or otherwise using the DSS.

6.2. Limitations of the study

Clearly results of this study are bound by the type of decision task, and characteristics of the DSS that was employed. While the current study found evidence of development and reliance effects, we can not conclude what parameter(s) caused this. The form and structure of a particular DSS seems likely to influence the presence and rate of learning by users. The DSS was developed using a readily available DSS generator, IFPS. While this DSS is representative of DSS in general, examinations of specific designs or parameters of DSS that promote development effects and minimize reliance effects appear to be warranted. Clearly, use of other types of DSS may yield substantially different results.

In addition, emphasis in the current study was placed on decision-making groups rather than individuals because of the nature of the decision task. Each group was competing only against other groups in their course section, all groups in a section were in the same experimental condition. Although each team member's grade was contingent on the team's overall performance, some social loafing by particular group members may have occurred within groups. Experimental designs using an individual level of analysis could help to determine the extent of potential reliance or development effects by individual decision makers, independent of group influences.

The decision task used in this study was complex and relatively unstructured. Interdependencies were present between the teams in an industry and uncertain economic and market conditions were present. While use of simpler, less complex decision tasks may result in different outcomes, DSS are designed primarily for such complex, ill structured decision problems.

6.3. Implications for research and practice

The results raise practical prescriptive issues in implementing DSS in organizations and suggest some areas for future research involving the use of decision aids for improving decision making. As noted earlier, longitudinal use of the DSS by the teams was sporadic. DSS can not be expected to affect decision performance positively unless it is utilized by the decision maker(s). Characteristics of the DSS itself may be crucial to the extent of usage. Cats-Baril and Huber [14] have suggested the importance of the 'interactiveness' of the decision aid. This factor may be a precursor to usage. A second potential method to encourage usage may be to allow users to participate in development of the DSS. In behavioral science literature, participation has often been found to lead to increased commitment, acceptance, and support [36].

We detected a reliance effect. This indicates that DSS was not totally effective in helping decision makers to understand the influence of the decision factors well. When the DSS was removed, performance decreased. In conjunction, this suggests a potential need to build the DSS at a higher cognitive level so that the DSS can assist the decision maker conceptualize the problem in addition to providing calculative support in decision-making. If the decision maker participates in building the DSS, this issue may be minimized. It is important to identify the necessary dimensions of 'fit' between decision maker, task and decision support system for the DSS to have maximum beneficial effects. Such issues become important in identifying necessary expertise required to make effective decisions and in modelling expert decision making.

The pattern of results suggests that it may be fruitful to incorporate more specific measures of decision *process* to capture the specific way(s) that DSS influence the decision making process. It is also important to relate particular decision processes to the establishment of development effects for DSS. This could facilitate the design of DSS to improve particular decision processes that lead to what we have referred to as 'development' effects.

Decision judgment is composed of three interrelated dimensions of information search, information combination and feedback or learning. Use of various process methods of cognitive mapping such as protocol analysis may assist in determining the effects of DSS on the intermediate decision process rather than the more traditional DSS-decision outcomes relationships examined in the majority of previous DSS research. In addition, the development of 'objective' measures in assessing decision makers' understanding of interrelationships between decision variables could assist in evaluating the presence and magnitude of development and reliance effects. This could allow for more comprehensive examination of relationships between DSS parameters, DSS usage/decision processes employed by decision makers and behavioral and affective decision outcomes.

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