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RESEARCH ARTICLE

Knowledge-based Support in a Group Decision Making Context: An Expert-Novice Comparison*

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Abstract

This research examines the use of knowledge-based and explanation facilities to support group decision making of experts versus novices. Consistent with predictions from the persuasion literature, our results show that experts exhibit a higher level of criticality and involvement in their area of expertise; this not only decreases their likelihood of being persuaded by a knowledge-based system, but also accounts for a lower group consensus among experts as compared to novices. Novices are more easily persuaded by the system and find the system to be more useful than experts do. This research integrates theories from the persuasion literature to understand expert-novice differences in group decision making in a knowledge-based support environment. The findings suggest that the analyses and explanations provided by knowledge-based systems better support the decision making of novices than experts. Future research is needed to integrate other types of information provision support (e.g., cognitive feedback) into knowledge-based systems to increase their effectiveness as a group decision support tool for domain experts.

Keywords: Knowledge-based Support, Group Decision Making, Experts versus Novices, Social Judgment-involvement Theory, Elaboration Likelihood Model

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Introduction

This paper describes an experimental research study that compares the use of a knowledge-based system and its explanation facilities to support small group decision-making of experts versus that of novices. Because knowledge is an important organizational asset and is regarded as the only source of sustainable competitive advantage (Drucker, 1995), organizations often find it useful to codify organizational knowledge and expertise in the form of knowledge-based systems in order to make them available for their own use (Lado and Zhang, 1998). Since the codification and development of such systems involve a large amount of time, effort, and organizational resources, it is important to understand and assess the effectiveness of a knowledge-based system (KBS) for supporting different types of end-users in group decision making.

Knowledge-based systems represent the knowledge and problem-solving expertise of human experts in narrow knowledge domains. A KBS provides two main types of support to its users: 1) *analyses* of the problem/case, and 2) *explanations* that provide knowledge and reasoning about what the system knows and does, how it works, and why its actions are appropriate (Swartout, 1987). The KBS used in this research provides both types of support to *complement* the knowledge of decision makers, but *not* to provide solutions to the problem (which is beyond the capabilities of KBS for highly complex problems). Similar to Luconi et al.'s (1986) concept of "Expert Support Systems" and Zopounidis et al.'s (1997) use of the term "Knowledge-based Decision Support Systems", this KBS is a *decision support*, rather than a *decision replacement*, tool.

Knowledge-based systems have helped firms not only to generate financial returns, but also to become strategically important (Gill, 1995; Lado and Zhang, 1998). A KBS can codify knowledge in a narrow domain and make it available to less-experienced decision makers and even support experienced ones (Luconi et al., 1986). A KBS can support both individuals and groups (e.g., Swann, 1988; Sviokla, 1989; Santhanam and Elam, 1998). For instance, at Imperial Chemical Industries, a KBS (so-called decision assistant system) that supports business planning has been used to assist in group decision making (Swann, 1988). Similarly, a group of financial planners at The Financial Collaborative has used a KBS called PlanPower to help them perform financial planning for their clients (Sviokla, 1989). Another example of group KBS use is support for commercial lending officers in their team-based decision-making process (Cross, 1997; Radigan, 1993; Strischek and Cross, 1996), which is similar to the task setting used in the experiment described in this paper. Since most of the important decisions in organizations are generally assigned to committees or task forces, and a KBS has the potential to provide support for groups, it is important to understand how KBS support influences group decision making by users with varying degrees of domain expertise. This is the first study to investigate how user expertise moderates the impact of KBS in *group* decision-making, which extends prior works on expert-novice differences to the group decision-making context. It explains how expertise differences can lead to different group decision outcomes, and proposes techniques to increase the effectiveness of KBS to support different groups of decision makers with varying degrees of domain expertise.

The rest of the paper comprises the following parts: a review of the related literature, the theoretical foundation and research hypotheses, the research method, the data analysis and research findings, the implications of the findings, and suggestions for future research.

Literature Review

This section reviews the empirical studies and literature on the use of KBS and their impact on experts and novices.

Empirical Studies on KBS Impact

A number of empirical studies have evaluated the various implications of KBS use. We refer the readers to Gregor and Benbasat (1999) for a detailed review of the use of KBS explanations in the individual context. Among the empirical studies on KBS use, only Sviokla (1989), Nah et al. (1999), Dasgupta et al. (2000), and Nah and Benbasat (2000) have examined the use of KBS in group settings. Sviokla (1986, 1989, 1990) carried out three case studies of KBS use in organizations – one of which examined KBS use in a group context. He focused more on the dynamics of the group processes than on group decision variables, such as group performance, the variable of interest in this study. The overall findings from Sviokla's studies suggest that KBS use increases the effectiveness and efficiency of organizations but at the expense of increased task rigidity. As a KBS was being used, maintained, and improved upon, problem solving knowledge improved and problem structure increased. Nah et al. (1999) compared the use of KBS for individual versus group decision making among novices who were knowledgeable and trained in the area. In both KBS and non-KBS support conditions, groups were found to outperform individuals, which signifies the benefits and important role of group decision making in organizations. Further, novice groups working with a KBS performed better than without one, suggesting that a KBS is an effective group decision support tool. Thus, the study shows that novice groups working with KBS outperformed all of the other conditions (i.e., novice groups without KBS, novice individuals with KBS, and novice individuals without KBS) due to the additive benefits of group and KBS effects (Nah et al., 1999). The effect of KBS on expert groups, which is the focus of this study, was less clear. Dasgupta et al.'s (2000) findings suggest that a KBS does *not* benefit novice groups in terms of performance, satisfaction, and confidence. Nah and Benbasat (2000) found that it was the explanation facilities, rather than the KBS analyses, that were mainly responsible for the shift in group judgments after KBS use. In this study, we assessed the impact of KBS in supporting group decision making among experts versus novices.

Literature on KBS Impact: Expertise Differences

The literature suggests that KBS is effective in both individual and group settings, and decision performance is highest when groups utilize KBS for decision-making. The literature discussed next also indicates that KBS support is expected to benefit novices more than experts in the individual decision-making setting.

Lamberti and Wallace (1990) found that a KBS has a greater impact on improving the performance of low-skilled users than high-skilled ones. Peterson (1988) found that a KBS improved the performance of users; however, this improvement in decision accuracy was greater for inexperienced users than for those who were experienced in the task domain.

Mao and Benbasat (2001) observed that novices, by virtue of requesting more deep (i.e., factual) explanations, were influenced more by the knowledge in the KBS than experts, and made decisions that were more congruent with those of the source experts whose knowledge was used to develop the KBS.

Anderson's (1982, 1999a, 1999b) *Adaptive Control of Thought* (ACT) and *Three-Stage Learning Model* can be used to account for the observed expert-novice differences in KBS impact as noted above. ACT introduces two main types of knowledge – declarative and procedural/production. Declarative knowledge refers to knowing that something *is* a fact (i.e., factual knowledge), and production knowledge refers to knowing *how* to do something (i.e., knowledge that leads to performance). According to ACT, experts generally possess both production (or procedural) and declarative knowledge, whereas novices generally have declarative knowledge but lack abstracted procedural knowledge. As such, novices rely more on declarative knowledge than procedural knowledge in problem solving, which explains why they are more influenced by deep (i.e., factual) explanations than experts (Mao and Benbasat, 2001). KBS analyses and associated explanations also help novices to overcome their lack of procedural knowledge. This explains why KBS impact is greater for low-skill/inexperienced users than for high-skill/experienced users (Lamberti and Wallace, 1990; Peterson, 1988).

The concept of expertise associated with ACT is further elaborated in Anderson's *Three-Stage Learning Model*. As one advances from a novice to an expert, one would be progressing from the "cognitive stage," to an intermediate stage called the "associative stage," and finally, to the "automatic stage." These three stages describe the degree to which one's production knowledge is automated. In the *cognitive stage*, a learner discovers relevant aspects of the task and stores declarative knowledge about skills. It takes effort to understand the task and to learn which information one must attend to. In the *associative stage*, cognitive processes become more efficient, allowing rapid retrieval and perception of required information. Thus, during the associative stage, skills are chunked, or compiled, into procedural knowledge. At the *autonomous or automatic stage*, performance is automatic, and conscious cognition is minimal. Novices perform at the cognitive or associative level, and require conscious cognitive effort and deliberate thinking in carrying out the task. Hence, KBS explanations that assist them in understanding the task domain could be very useful (Mao and Benbasat, 2000). On the other hand, Mao and Benbasat (2000) suggest that experts, compared to novices, are less likely to find KBS support useful, as experts' problem-solving processes have become automated, causing them to be less likely to take into consideration or to accept advice from KBS.

Theoretical Foundation and Hypotheses Development

In this research, we use a construct called *congruence* to assess the persuasive influence of KBS. Congruence is defined here as the *degree of similarity* between the judgments made by the KBS users and those made by the knowledge-source experts (i.e., experts whose knowledge were used to develop the KBS). We expect that the utilization of KBS analysis and explanation support, which reflect the knowledge of the source-experts, will influence a group's judgments toward those of the knowledge-source experts and result in increased congruence between them. Figure 1 illustrates the congruence construct, which is discussed in more detail in Section 4.

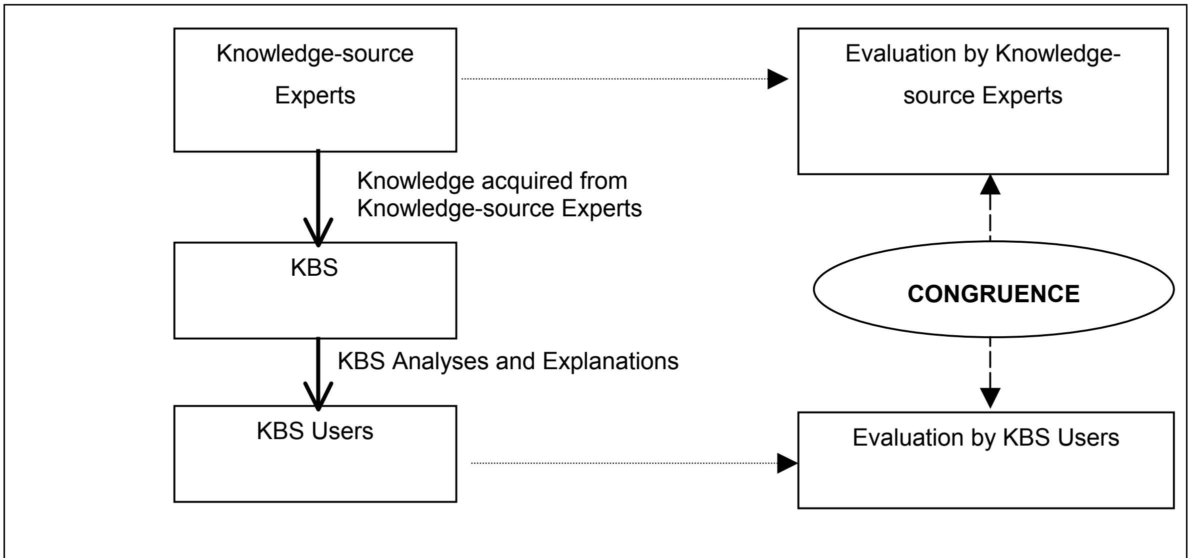

Figure 1. Congruence

One general theory that discusses the conditions that lead to behavior change as an outcome of persuasive communication is Petty and Cacioppo's (1981, 1986) *Elaboration Likelihood Model* (ELM). ELM was used in an earlier study to predict the differential impact of different levels (or types) of KBS support on congruence of group decisions (Nah and Benbasat, 2000). The current study, however, focuses on how KBS analyses and explanations affect congruence differentially for novice and expert decision makers in group settings. Both ELM and *Social Judgment-involvement Theory*[1] (SJIT) are used to generate the hypotheses for this research and to explain differences in group decision-making behavior between experts and novices provided with a KBS.

According to ELM, persuasion can take place via two routes – central and peripheral – based on the *moderating* effects of *ability* and *motivation* for elaboration. With a higher ability and knowledge structure to process information, experts are more likely to take the *central* (rather than the peripheral) route to persuasion because their likelihood of cognitive elaboration is higher. The central route occurs when thoughtful consideration of the persuasive message takes place, while the peripheral route refers to a response induced by cues that do not necessitate scrutiny of the central merits of the message (Petty and Cacioppo, 1986). Although experts typically also possess higher motivation for elaboration, the nature of their processing can be biased by their *ego-involvement* (Sherif and Cantril, 1947; Wood et al., 1995; Biek et al., 1996). Ego-involvement has important motivational and affective consequences that can result in biased or defensive processing and strong initial attitudes that are resistant to change (Johnson and Eagly,

[1] *Social Judgment-involvement Theory* (Sherif et al., 1965) is more commonly known as *Social Judgment Theory* in the persuasion literature. We use the term Social Judgment-involvement Theory to differentiate it from Hammond's Social Judgment Theory. We thank the anonymous reviewer for this suggestion.

1989; Wood et al., 1995; Biek et al., 1996). Because the attitudes of experts are based on extensive internal structures (Eagly and Chaiken, 1995), any change in such attitudes must be accompanied by the corresponding change in structure, or else cognitive dissonance (Festinger, 1957) will result. Thus, experts take resisting efforts to maintain their strong attitudes.

The SJIT and related subsequent research by Wood et al. (1995) and Biek et al. (1996) emphasize how one's prior attitudes and ego-involvement (strong affect/value) influence one's processing of a new persuasive message. Because experts possess special skills, knowledge, and experience in a particular domain, they would feel annoyed or even "threatened" if their status or ideas were challenged. SJIT suggests that exposure to discrepant attitudes creates a great deal of psychological discomfort for the ego-involved person (Sherif and Sherif, 1967, p.130), who encodes attitudinal information in a highly personalized and self-protective manner. Because experts are more likely to exhibit high affect or ego-involvement toward their judgments, they are more likely to use their existing knowledge to bolster and protect existing evaluations rather than accept new ones that may threaten their self-concept. Hence, according to ELM, experts will critically evaluate new persuasive messages (i.e., via the central route); but they are more likely to do so in a biased or defensive manner, as suggested by SJIT. We, therefore, hypothesize that group judgments made by domain experts will be less congruent with those of the knowledge-source experts than group judgments made by novices, because novices are more likely to accept and agree with the analyses and advice given by the KBS.

Hypotheses 1: With KBS support, group judgments made by experts will be less congruent with those of the knowledge-source experts than group judgments made by novices.

Similarly, research on SJIT suggests that experts tend to be critical not only with KBS but also among themselves, thus making it more difficult to achieve true consensus when compared to novices. Because domain experts are, in general, more critical and more likely to disagree with one another's judgments, we hypothesize that groups comprised of domain experts will reach a lower level of group consensus than groups comprised of novices.

Hypotheses 2: With KBS support, groups comprised of domain experts will achieve a lower level of group consensus than groups comprised of novices.

Since experts are less likely than novices to yield to and accept the analyses and explanations given by KBS (see earlier discussion), experts will perceive KBS to be less useful. On the other hand, novices, being less critical and more receptive to KBS support, are more easily persuaded by KBS. Novices can be persuaded by KBS via the central and/or the peripheral route. Novices may buy-in to the analyses or explanations given by the KBS because of its perceived expertise or credibility (i.e., peripheral route), or may utilize the analyses and explanations in the KBS to facilitate their understanding of the case/problem (i.e., central route). Therefore, novices will perceive KBS to be more useful than experts do.

Hypotheses 3: Novices will perceive KBS to be more useful than experts do.

Research Method

We conducted a laboratory experiment to test the research hypotheses in a KBS-supported group decision-making context. The task was a financial analysis case involving the evaluation of a commercial loan application by a hypothetical firm called Canacom. We provided all subjects with five years' financial statements of the firm, financial ratios derived from the statements, and information on the purpose and size of the loan requested. We asked the subjects to assume the role of corporate loan officers to assess various aspects of the firm's financial health.

The subjects were required to answer six questions about the strengths and weaknesses of the company's financial condition. These questions asked the subjects to rate, on a scale of 1-10, the liquidity, long-term solvency, asset utilization, value of stock as collateral, quality of financial management, and quality of operating management of the company.

Experimental KBS

For experimental control, we used a simulated KBS named FINALYZER that we adapted from an earlier study (Dhaliwal, 1993). FINALYZER was developed based on the knowledge and reasoning processes of six senior financial analysts, whose related experiences ranged from 12 to 23 years. These analysts were given the same commercial loan evaluation case to analyze as the one given to the subjects in this study. We collected their (individual) concurrent verbal protocols to determine the types of analysis that they performed and their detailed reasoning processes and explanations. We also captured their problem-solving processes and used these as the basis for developing FINALYZER, which is comprised of a series of sub-analyses.

To validate the system, two accounting professors, three doctoral students in accounting/finance, and two junior financial analysts used the KBS. None of them were able to detect that it was not a fully functional KBS. The system was used several times in prior research (e.g., Mao and Benbasat, 2001), and was considered highly realistic and useful by the subjects (Dhaliwal, 1993), who also rated very highly the level of expertise it displayed.

The experts whose knowledge was used to develop the KBS (labeled as *knowledge-source experts*) were also asked to provide a "solution" to the six judgmental questions involved in the experimental task. After a two-round Delphi process we took the final set of scores agreed upon by the knowledge-source experts as a benchmark of the "correct" judgments for the case. These consensus scores were retained as the benchmark solution for assessing decision congruence of the users (i.e., subjects for this study), and are indicated in Figure 1 as "Evaluation by Knowledge-source Experts."

As a decision support tool for a semi-structured (financial analysis) task, the KBS does **not** provide solutions to its users. Instead, it provides analyses and explanations that are in line with the *consensus judgments of the knowledge-source experts*. In FINALYZER, each conclusion or recommendation has three types of *reasoning-trace explanations* that describe the problem-solving process of the system (Mao and Benbasat, 2001). These reasoning-trace explanations reveal: 1) why the recommendation is relevant and important (Why explanation), 2) how the recommendation has been reached (How explanation), and

3) the strategic relationship between the recommendation and other conclusions in relation to the goal (Strategic explanation).

In addition to reasoning-trace explanations, we also provide *deep explanations* underlying generic domain knowledge for each of the concepts used in financial analysis. Three types of deep explanations for each concept are available (Mao and Benbasat, 2001): 1) its definition (How explanation), 2) why it is useful and important (Why explanation), and 3) relationships with other concepts involved in the same task (Strategic explanation). Appendix A shows examples of the KBS analysis (or recommendation) screens and the reasoning-trace and deep explanations. Note that Why, How, and Strategic explanations are available for each of the deep and reasoning-trace explanations.

FINALYZER performs financial analysis in terms of several sub-analyses such as liquidity, capital structure, and profitability. It provides three types of screens (Figure 2) for each of the sub-analyses: 1) an *information screen* containing an index of domain concepts (financial ratios and procedures), for which users can request deep explanations, 2) a *data screen* of relevant financial ratios calculated from the financial statements of the firm to be evaluated, and 3) *recommendation screens* presenting the results of the "evaluation" of the financial statements and ratios, in the form of recommendations. Users can request reasoning-trace explanations for each of the recommendations. The sequence of the screens is shown in Figure 2, which is consistent with the normal procedure of financial analysis, i.e., calculating financial ratios first and then yielding judgments for making decisions and predictions.

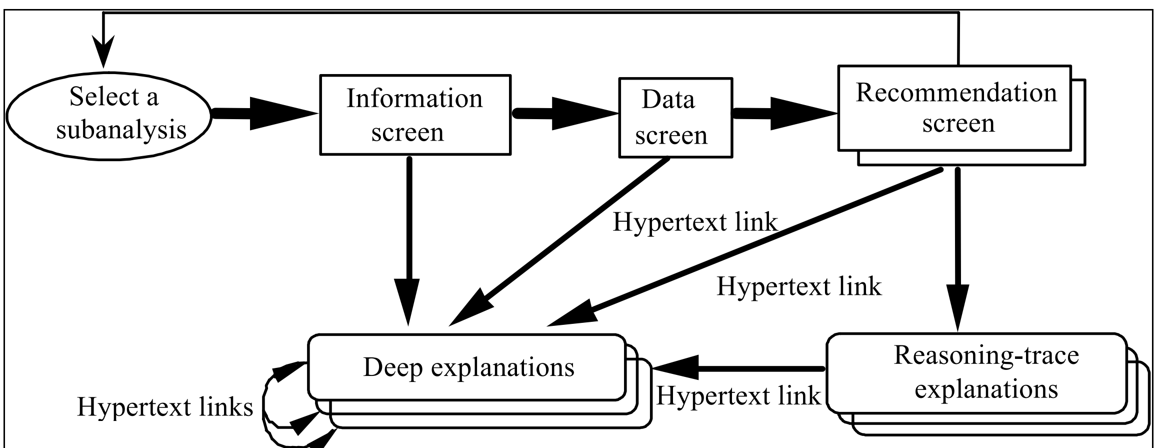

Figure 2. Flow Chart of FINALYZER

Furthermore, FINALYZER allows *contextualized access* to deep explanations via hypertext-style links. Contextualized access makes deep explanations available not only through the data screen *prior* to the analysis, but also from system recommendations and reasoning-trace explanations. When examining deep explanations, users can access explanations on related domain concepts by following the hypertext-style links. Deep explanations are not only linked to other related deep explanations but also integrated into other parts of system output (i.e., reasoning-trace explanations and recommendations).

Subjects

Two groups of subjects were involved in this research: experts and novices. Since specialized skills related to advanced accounting and financial statements analysis were needed to carry out the financial analysis task, we recruited only subjects knowledgeable in accounting in order to increase the generalizability and validity of the study. The expert subjects were experienced professionals whose work involved financial analysis and whose job responsibilities include making commercial loan decisions on a regular basis (daily or very frequently) in major financial institutions. Hence, they satisfy Camerer and Johnson's (1991) definition of experts, referring to those who are experienced and have some professional or social credentials in the domain. The novice subjects included business seniors and MBA students who either specialized in accounting or had taken accounting courses extensively. They had conceptual domain knowledge on financial analysis but had no *practical* experience in its performance. These novices were different from laypersons, or people with little or no specialized skill in the domain area. Instead, they were "educated novices," similar to entry-level employees for financial analysis positions. A total of 27 novice subjects (9 groups of 3) and 18 expert subjects (6 groups of 3) participated in the study.

As a manipulation check, we captured the subjects' self-rating of their competence as a financial analyst in the background information questionnaire by asking: "How do you rate yourself as a financial analyst (of a corporate loan decision)? (1– Excellent, 2 – Good, 3 – Somewhat good, 4 – Fair, 5 – Somewhat poor, 6 – Poor, 7 – Bad)" The average rating of the novice subjects was 3.8 and that of the expert subjects was 1.9. The difference is statistically significant at $p<0.01$. This supports our operationalization of the expertise construct. For the expert subjects, the average number of years of work experience related to financial analysis was 13.3. Hence, based on the years of experience, the expert subjects were generally less experienced than the knowledge-source experts whose knowledge was used to develop the KBS.

Experimental Procedures

Figure 3 shows the experimental procedures. We randomly assigned the novice subjects from the same sections of accounting courses to groups of three. We also randomly assigned the expert subjects working for the *same* financial institution to groups of three.

The subjects first completed the consent forms and background information questionnaires. They were next given the relevant financial information of the company to be evaluated. They worked on the case *individually* and *without* any form of KBS support, and produced a set of individual judgments on the six questions.

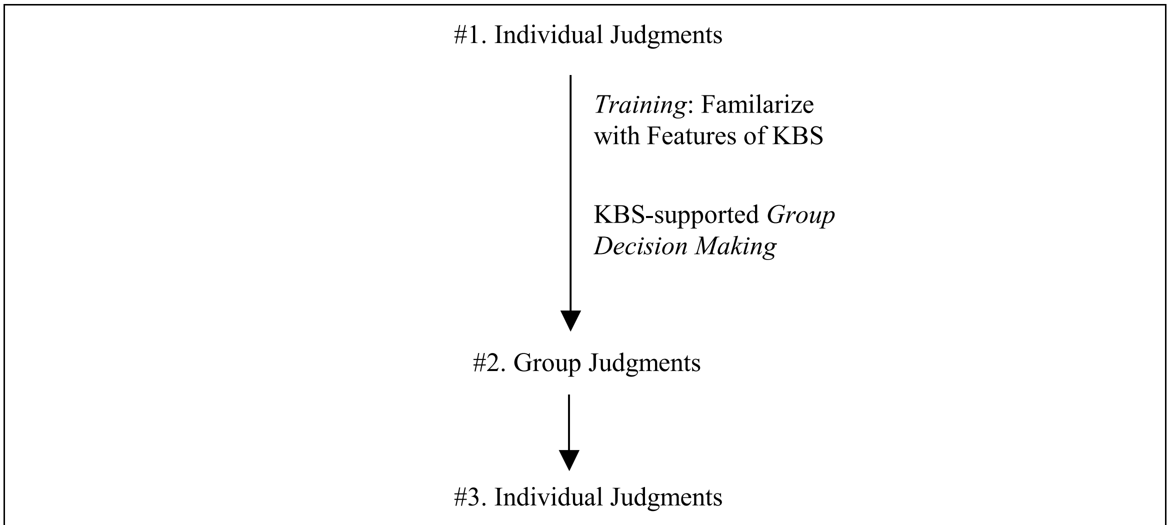

Figure 3. Research Procedure

Subjects were then provided with the appropriate training to familiarize them with the features of the KBS. For the training session, we used a system for evaluating consumer credit applications that has features similar to the experimental KBS. Next, the subjects worked in their assigned groups of three until they reached a group consensus on the same set of judgments they had made earlier. Finally, they were asked to make the same set of judgments again *individually*, taking into account what they had learned from their group discussions and the KBS. The final individual judgments allowed us to evaluate the degree of true consensus in each decision-making group. We captured the perceived usefulness of the KBS using a questionnaire administered at the end of the experiment (see Appendix B).

The group members used the KBS in a face-to-face context (see experimental setup in Figure 4). A "chauffeur" carried out the verbal requests from the group to access the KBS analyses and explanations, so that no one member could "dominate" the process by controlling the mouse.

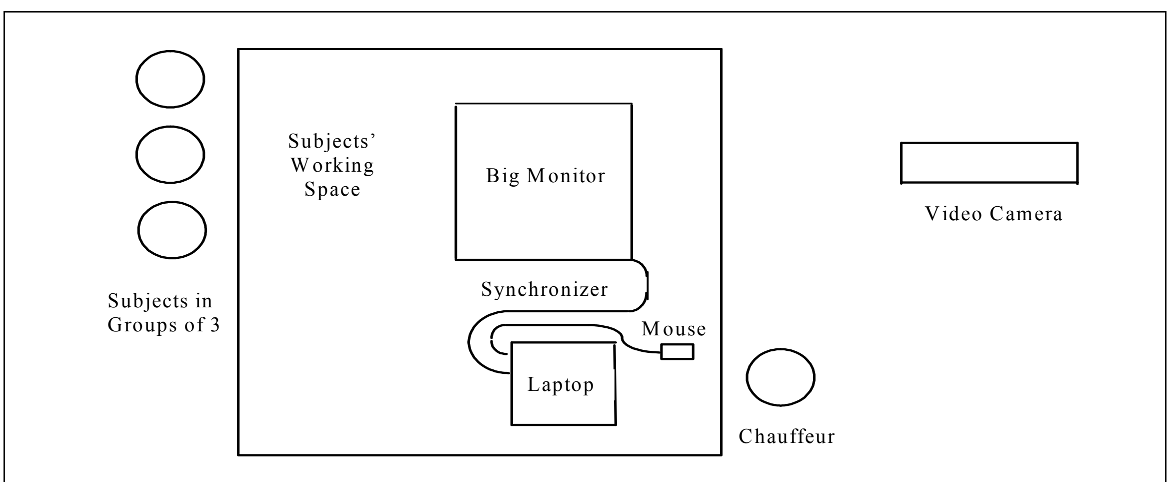

Figure 4. Experimental Setup

Measures for Dependent Variables

We assess the level of **congruence** for each of the six judgments by its absolute deviation (or distance) from the consensus judgment of the knowledge-source experts:

$$D_i = |G_i - S_i| \qquad i=1,2,\ldots,6$$

where D_i is the absolute deviation of the group judgment from the consensus judgment of the knowledge-source experts for the ith question, G_i is the group judgment on the ith question, and S_i is the consensus judgment of the knowledge-source experts on the ith question. The total deviation score, D, is the sum of the absolute deviations of these six group judgments from the consensus judgments of the knowledge-source experts:

$$D = \sum_{i=1}^{6} D_i$$

Therefore, *the lower the total deviation score, the closer are the group judgments to the consensus judgments of the knowledge-source experts, and hence, the higher the decision congruence*.

We assess group **consensus** in two ways: (1) consensus in group judgment is the sum of the absolute deviations between each group member's individual post-discussion judgment and the group judgment; (2) consensus among individual post-discussion judgments is the sum of the absolute deviations between every two members' individual post-discussion judgments.

We assess consensus in group judgment as follows:

$$Cg = \sum_{i=1}^{6} \sum_{k=1}^{3} |(G_i - J_{ik})|$$

where G_i is the group judgment on the ith question, and J_{ik} is the final (post-discussion) individual judgments on the ith question by the kth member of the group. Therefore, *the lower the total score (Cg), the higher (better) the level of consensus in the group.*

We assess consensus among individual post-discussion judgments as follows:

$$Cp = \sum_{i=1}^{6} \sum_{1 \le k < q \le 3} |(J_{ik} - J_{iq})|$$

where J_{ik} is the final (post-discussion) individual judgments on the ith question by the kth member of the group. Therefore, *the lower the total score (Cp), the higher (better) the level of consensus in the group.*

The perceived usefulness of KBS refers to the degree to which users perceive the KBS to enhance their task performance. The scale for Perceived Usefulness of KBS was adapted and modified from the instrument developed by Dhaliwal (1993), which was an adaptation of the instruments from Moore and Benbasat (1991) and Davis (1986). Since Dhaliwal's (1993) study was carried out in the individual context, the scale was slightly modified to suit the *group* context. We included the instrument as part of the post-study questionnaire administered to the *individual* subjects. The items in the scale are presented in Appendix B. Based on the data collected in this study, the perceived usefulness scale had a Cronbach's alpha coefficient of 0.93.

Findings

Quantitative analyses were carried out to compare the congruence of group judgments, group consensus, and perceived usefulness of KBS between experts and novices. Since this study looks at group decision making, the default unit of analysis is at the group level. In order to take into account the possible group effect, for measures captured at the individual level (e.g., perceived usefulness of KBS), we use the nested hierarchical ANOVA design when parametric assumptions are not violated. On the other hand, for measures at both the individual and group levels, we use the Mann-Whitney *U* test, a *non-parametric* test (Siegel and Castellan, 1988), to analyze the data at the group level when assumptions of the parametric tests are not met (Neter et al., 1996).

Congruence in Group Judgments

The first hypothesis compares the group judgments (#2 in Figure 3) of experts to those of novices in terms of their level of congruence. Since the distribution of the total deviation scores does not meet the normality assumption, we used the Mann-Whitney *U* test for the analysis. Table 1 shows the descriptive statistics while Table 2 presents the results of the Mann-Whitney *U* test.

Table 1. Descriptive Statistics – Congruence of Group Judgments

Source	N	Mean	Std. Dev.	Std. Error	Min	Max	Range
Experts	6	6.8	1.6	.65	4	8	4
Novices	9	4.9	2.1	.70	3	8	5
Total	15	5.7	2.1	.54	3	8	5

Table 2. Results of Mann-Whitney *U* Test – Congruence of Group Judgments

Source	N	Mean Rank	Sum of Ranks	Mann-Whitney *U*	*p*-value (1-tailed)
Experts	6	10.4	62.5	12.5	.04
Novices	9	6.4	57.5		

The results of the Mann-Whitney *U* test indicate that experts were less likely than novices to buy-in to KBS analyses and advice ($p<.05$). Hence, Hypothesis 1 is supported.

We carried out a test to assess if the observed difference could be attributed to differences in extremity of the initial judgments. To do so, we compared the congruence levels of the initial (pre-discussion) individual judgments (#1 in Figure 3) of experts with those of novices (at both the individual and group (i.e., aggregated by group) levels). Since the assumptions for parametric tests were satisfied, we used *t* tests for the analysis. The congruence level of the initial judgments of the expert subjects is not statistically different from those of the novice subjects when analyzed at both the individual level (*t* test: p=0.53 (2-tailed)) and the group level (*t* test: *p*=0.67 (2-tailed)). Hence, there was no difference in the congruence of initial individual judgments between the experts and novices, ruling out position extremity as a possible cause. This validation check also shows that the novice subjects were knowledgeable in the task domain, as they were trained in the accounting domain and had the prerequisite domain knowledge on financial analysis.

Group Consensus

The second hypothesis compares the level of group consensus between experts and novices. Recall that we use two measures of group consensus – consensus in group judgment, and consensus among individual post-discussion judgments. Since data analyses using both measures produce similar results, we present the results for 'consensus in group judgment' only. The descriptive statistics are presented in Table 3. The Mann-Whitney *U* test was used because the distribution violates the normality assumption. The results of the Mann-Whitney *U* test are shown in Table 4.

Table 3. Descriptive Statistics – Group Consensus

Source	N	Mean	Std. Dev.	Std. Error	Min	Max	Range
Experts	6	9.7	1.6	.67	8	12	4
Novices	9	4.9	4.1	1.37	1	15	14
Total	15	6.8	4.1	1.05	1	15	15

Table 4. Results of Mann-Whitney *U* Test – Group Consensus

Source	N	Mean Rank	Sum of Ranks	Mann-Whitney *U*	*p*-value (1-tailed)
Experts	6	11.5	69.0	6.0	.01
Novices	9	5.7	51.0		

The results support Hypothesis 2, which indicates that the level of group consensus is better among the novices than the experts (*p*<.05). To verify that the observed difference arose during or after (and *not* before) KBS-supported group discussions, we carried out a pre-test to compare the level of consensus within a group based on the initial (pre-discussion) individual judgments (#1 in Figure 3) of the experts and novices (i.e., with group as the unit of analysis). Since the distribution violates the normality assumption, we used the Mann-Whitney *U* test for the analysis. The results show that there was no difference in the *initial* (before KBS use) level of consensus between the expert and novice groups (*p*=.52), indicating that the observed difference in level of consensus came about during or after the KBS-supported group discussions.

Perceived Usefulness of KBS

The third hypothesis compares the perceived usefulness of KBS between experts and novices. Since perceived usefulness of KBS was measured at the individual level, the nested hierarchical ANOVA design is most appropriate for the analysis (Anderson and Ager, 1978). The primary aspect of this design is the assumption that an individual's score is in part influenced by the *social unit* to which he or she belongs. In this study, subjects were assigned to (and therefore nested within) groups of three, which were nested within expertise. Therefore, the total variability among subjects has three potential sources: treatment (expertise) effects, group effects, and residual individual differences (subjects within the same group may vary due to such factors as attitude or ability).

Since the distributions for perceived usefulness of KBS satisfy the parametric assumptions, we used the nested ANOVA design for the analysis. We present the descriptive statistics in Table 5 and the results in Table 6.

Table 5. Descriptive Statistics – Perceived Usefulness of KBS

Source	N	Mean	Std. Dev.	Std. Error	Min	Max	Range
Experts	18	4.7	1.2	0.28	1.9	6.1	4.2
Novices	27	5.5	0.7	0.14	4.3	7.0	2.7
Total	45	5.2	1.0	0.15	1.9	7.0	5.1

Table 6. Results of Nested ANOVA – Perceived Usefulness of KBS

Source	SS	DF	MS	F	*p*-value
Expertise	413.2	1	413.2	5.5	.04
Group within Treatment	985.4	13	75.8	1.6	.14
Error	1420.0	30	47.3		

The results support Hypothesis 3, which indicates that the novices perceived KBS support to be more useful than the experts did ($p<.05$).

Discussion and Conclusions

This research extends earlier studies on KBS by investigating the effectiveness of KBS in a group setting for decision makers of different levels of expertise. It shows that expertise is a key factor moderating the effectiveness of KBS. Given that the skills of the professional financial analysts who participated in our study are highly valued in the financial industry, they tend to be highly ego-involved in their area of specialization (Sherif and Cantril, 1947; Sherif, et al., 1965; Sherif and Sherif, 1967). The study results are consistent with ELM and SJIT, which suggest that experts are more likely to critically evaluate KBS conclusions and to utilize their knowledge to defend their initial opinions. For instance, one expert, after reading a KBS conclusion indicating that "the company was following a policy of accepting lower asset turnover for higher profit margin," disagreed:

> "*I think that's a dangerous conclusion to say that one (higher profit margin) follows from the other (lower asset turnover). They are accepting a lower asset turnover, that's no question. But that doesn't mean that's why they're generating a higher profit margin. They could be generating a higher profit margin because they have a better computer. And the fact that they have lower turnover is just bad management. So, I appreciate that may be the case, but it's certainly not an easy conclusion to draw.*"

Although KBS has a more pronounced impact on novices in their group decision making, it is not clear if KBS is an effective tool for supporting group decision making among experts. To address this question, we assessed the degree of improvement in group decision congruence of both experts and novices. As presented in Table 7, the average improvement in congruence of group judgments (from congruence of the group average of individual pre-discussion judgments) is 4.26 for novices and 1.73 for experts, indicating that the KBS exerted a greater influence on the novices than on the experts. The Wilcoxon signed ranks test shows that the improvement in experts' group decision congruence is marginally significant ($p=0.07$), while that of the novices is highly significant ($p<0.01$). Hence, further research is needed to assess the degree of effectiveness of KBS for supporting group decision making among experts and to incorporate other feedback and cognitive support features to increase KBS effectiveness (see the last section of this paper).

Table 7. Descriptive Statistics – Change in Congruence Level of the Group Judgments from the Group Average of Individual Pre-discussion Judgments

Source	N	Mean	Std. Dev.	Std. Error	Min	Max
Experts[2]	5	1.7	1.5	.50	-1.0	3.7
Novices	9	4.3	1.9	.87	2.3	6.3
Total	15	3.4	2.1	.54	-1.0	6.3

The results show that experts not only exhibited a lower level of acceptance of KBS conclusions when compared to novices, but they were also less likely to agree with their expert peers. In other words, experts tend to be critical not only with the analyses and advice of the KBS, but also among themselves. Because expert decision makers are generally more critical than novices in evaluating and accepting recommendations given by their peers, they achieve lower group consensus than novice decision makers.

Perceived usefulness is an important variable in IS research as it strongly influences users' intentions to use a system (Davis et al., 1989), which in turn influences actual usage of the system (Moore and Benbasat, 1996; Taylor and Todd, 1995). KBS was perceived to be more useful by novices than by experts in improving task performance

[2] Only 5 cases were considered because one of the subjects did not specify one of his/her individual pre-discussion judgments.

that was carried out in groups, suggesting that novices are more likely than experts to use a KBS.

Based on the ELM and SJIT, we can explain the observed outcomes of this study as follows: the novices were more receptive to KBS advice and explanations due to its perceived credibility and expertise (i.e., peripheral cues) as well as the information processing support (i.e., central route). They were able to utilize the system to make group decisions that are in line with the system and to reach a higher level of group consensus. On the other hand, the experts were more critical in information processing (i.e., taking a central route to persuasion) because of their ego-involvement in the decision-making process (i.e., due to the high relation between the task and their ego) and their strong attitudes arising from their highly structured and elaborated knowledge schema (Wood et al., 1995). In order for experts to change their opinions, they need to identify and understand the corresponding change in their knowledge schema, or cognitive dissonance will result. Thus, experts do not yield easily to the advice and explanations offered by the KBS or other members of the group. Compared to the group judgments of novices, the group judgments of experts were achieved with a lower level of true consensus and were less congruent with those of the knowledge-source experts. Hence, experts did not find the KBS to be as useful as the novices did.

Limitations of Study

There are several limitations in this research. First, we faced significant difficulties recruiting *experts* for this study. After contacting several financial institutions, we were able to find 18 experienced financial analysts from two major financial institutions (nine from each institution) who agreed to participate in the study. According to Siegel and Castellan (1988), the sample size we have (i.e., 6 groups of three for experts) is adequate for non-parametric statistical analysis, which requires a minimum of 5 data points per cell (unlike the case of parametric analysis, which requires 10). As shown in our data analysis, all three hypotheses were supported (i.e., statistically significant differences were observed), indicating that statistical power is not an issue in this study (as the effect size is large).

Another possible limitation of this study is its generalizability. Since this study was conducted in a laboratory setting, it is possible that subjects may behave differently when making such decisions in a real setting. Because this experiment was conducted in a face-to-face context, the results may not be generalizable to *non* face-to-face settings. Future research is needed to evaluate if experts and novices would approach the use of KBS differently in a non face-to-face group decision-making setting, and how such differences (if any) may impact on group decision making.

Third, since this is a one-time cross-sectional study, the possibility of novelty effect cannot be ignored. Because each experimental session lasted about three hours (due to the nature of group decision making), we were not able to ask the subjects to analyze another case without sacrificing reliability and validity (e.g., fatigue would arise). Although it would have been possible to arrange follow-up sessions for the same group of subjects, attrition was an issue – particularly since all three subjects in a group must be present to conduct the session. However, we took a number of measures to minimize the novelty effect. Before the subjects began to use the experimental KBS, we provided them with a training session to familiarize them with the features of a similar KBS. We also provided them ample time to familiarize themselves with the case (during the initial individual decision-making phase) and the KBS (during the training session) in order to minimize the cognitive load and complexity involved in using the KBS.

Implications for Research and Practice

In this study on group decision making, novices were found to be more willing than experts to accept KBS advice. Lamberti and Wallace (1990) and Peterson (1988) also made the same observation for individual decision makers. Additionally, novices believed that the KBS was more useful in improving group decision-making effectiveness. These findings are consistent with theories in persuasion, which predict that novices are more willing to accept advice from external sources. But to accept such advice, novices should also believe in the veracity of the advice they are receiving. From earlier research (Nah and Benbasat, 2000), we know that for novices, the provision of **both** KBS explanations and advice (as was the case in this study) is necessary for accepting KBS analyses and advice and increasing decision congruence. Explanation facilities are likely to enhance users' trust in the KBS, because they increase users' comprehension of KBS advice and reasoning, and the perceived technical capability demonstrated by the KBS. Explanations also increase the force and diversity of arguments that support the KBS analyses and advice, thus making the specific messages (advice) provided by the KBS more believable. According to ELM, the availability of explanations is even more important for experts because they are more likely to rely on the central route to yield to the KBS. But what kinds of explanations are most effective?

To address this question, we draw on Eagly and Chaiken's (1995) recommendations on techniques to overcome strong attitudes and resistance to change due to extensive working knowledge and ego-involvement. They state that change techniques can be understood in terms of their impact on intra-attitudinal and inter-attitudinal structures. From the perspective of *inter-attitudinal* structure, an attitude can be changed by decoupling it from other attitudes to which it is attached, especially from the more *abstract* attitudes from which it may have been deduced. From the above reasoning, deep explanations are likely to be more useful than reasoning-based explanations in changing strong attitudes. *Deep explanations* justify KBS output by linking it to a causal model of the underlying knowledge, i.e., deep knowledge (Southwick, 1991). Deep explanations are presented at the *abstract* level, unlike reasoning-trace explanations that are specific to particular outcomes. Hence, deep explanations have a greater potential to change the underlying inter-attitudinal structure of users by de-coupling mistakenly linked attitudes from one another, and coupling alternative relationships among abstract attitudes that may have been overlooked by decision makers.

Another feature that may be helpful in changing experts' attitudes to achieve a higher (better) consensus in decision making is cognitive feedback (Sengupta and Te'eni, 1993). Cognitive feedback refers to information about the decision makers' cognitive processes. Such information is intended to resolve cognitive conflicts that may arise due to cognitive limitations or the lack of a common understanding of the problem by the members of a group. Cognitive feedback has been shown to be effective in improving control and convergence (i.e., consensus) in the group setting (Sengupta and Te'eni, 1993). For supporting group decision making among experts, the provision of cognitive feedback in addition to KBS support may help to facilitate consensus building among the experts.

From the perspective of *intra-attitudinal* structure, change is most effective when people are provided with a very large amount of new experience with the attitude object (Eagly and Chaiken, 1995). In other words, Eagly and Chaiken recommend that the 'targeted' people be exposed to a large amount of information consistent with the desired attitudes. In this case, the most effective information is feedback on the outcomes of the decision-making process. The importance of the dynamic nature of environmental feedback in human decision behavior, i.e., the impact of a decision made on the external environment including the firm, cannot be neglected (Powers, 1973; Hogarth, 1981). If experts, based on outcome feedback, are convinced of the appropriateness of the recommendations provided by a KBS, then they will form favorable attitudes toward the KBS, and their resistance will be reduced. Therefore, in addition to the task information and reasoning provided by the KBS, outcome feedback can be provided and integrated into the overall support system that includes the KBS (Tindale, 1989).

The accumulated knowledge from several studies (e.g., Nah et al., 1999; Mao and Benbasat, 2001) on KBS and explanation use leads to the following observations about the "transfer" of knowledge from a KBS to its users:

> **Benefits of KBS Use**: KBS use benefits *both* individuals and groups, that is, individuals (or groups) provided with KBS support exhibit higher decision congruence than individuals (or groups) without KBS support (Nah et al., 1999).
>
> **KBS Use by Individuals versus Groups**: G*roups* with KBS support are able to achieve higher decision congruence than *individuals* with KBS support. Taking into account the previous point concerning the benefits of KBS for both groups and individuals, groups with KBS support make the best decisions (Nah et al., 1999).
>
> **Individual Differences:** Novices are more strongly influenced by the deep explanations they receive from KBS than experts (Mao and Benbasat, 2001). However, the effectiveness of deep versus reasoning-trace explanations for experts has not been tested. Similarly, Mao and Benbasat (2001) also observed that KBS support is more influential for novices than experienced professionals.

In summary, KBS appears to be less influential for experts, either in groups or as individual problem solvers. In this paper, we provided an explanation as to why this is the case, based on the ELM and SJIT. Although we have provided some recommendations on support features that might help increase the effectiveness of KBS for experts, the open research questions that remain are: (1) whether such support features are effective in changing the strong attitudes of experts, (2) whether additional support features that can benefit expert decision makers can be identified, and (3) whether such attempts are bound to be dysfunctional by creating an adverse reaction on the part of the experts. Future research is needed to answer these questions.

The quantitative results and anecdotal evidence from this study indicate that expert subjects exhibited a strong critical stance toward the KBS, even when this use was for an academic study; one would expect a more adverse reaction if such use was suggested in one's work setting. ELM (Petty and Cacioppo, 1981, 1986) predicts that explanations support is necessary to convince and persuade experts to accept conclusions provided by KBS, whereas novices may be persuaded based partly on the perceived credibility (expert power) of the KBS. The benefits of providing KBS explanations to novices have been empirically verified in an earlier study (Nah and

Benbasat, 2000). Therefore, a potentially promising avenue to identify how to promote KBS use by expert decision makers is to focus on the types of explanations and decision feedback that they should be provided to convince them to accept the analyses and advice advocated by KBS and to reach better convergence in their group decisions. Future research should examine not only how to change or influence experts' acceptance of KBS but also how to increase the effectiveness of group decision making by having experts take into account each other's differing opinions and perspectives. Providing other types of information support, such as cognitive and outcome feedback, as discussed earlier, may be helpful in these two aspects.

In summary, the contributions of this research can be viewed from both the empirical and theoretical perspectives. From an empirical perspective, this research extends the use of the knowledge-based technology to the group context. It offers empirical evidence of KBS support for *group* decision making among experts versus novices. It also provides suggestions to improve KBS support for group decision making. From a theoretical perspective, this research links KBS research with group decision-making and persuasion theories. We believe the integration of persuasion theories with empirical evaluation of group decision making by experts versus novices is an important and unique contribution to the existing literature.

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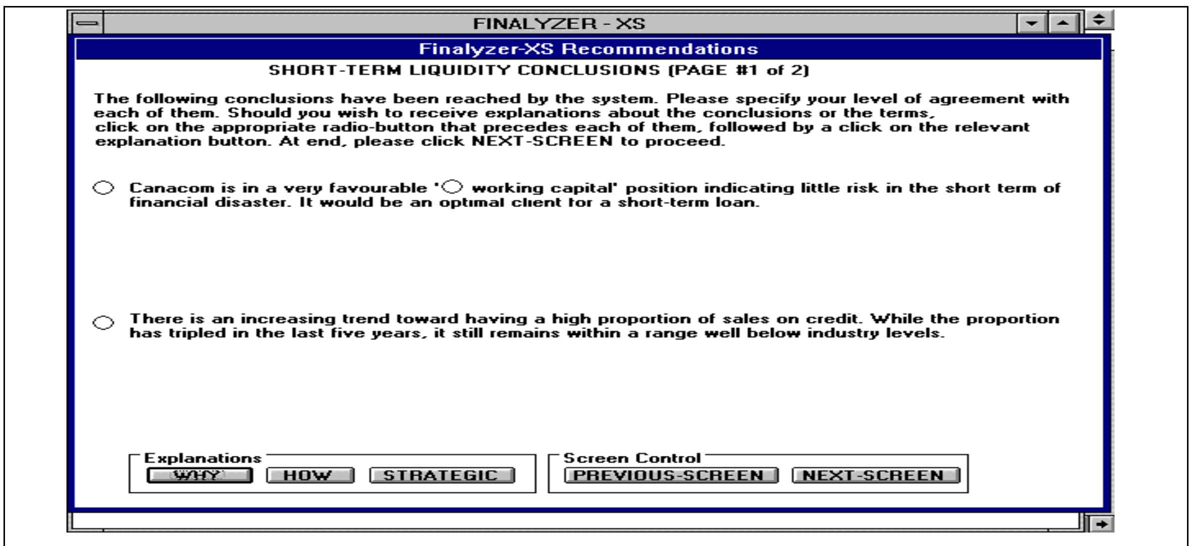
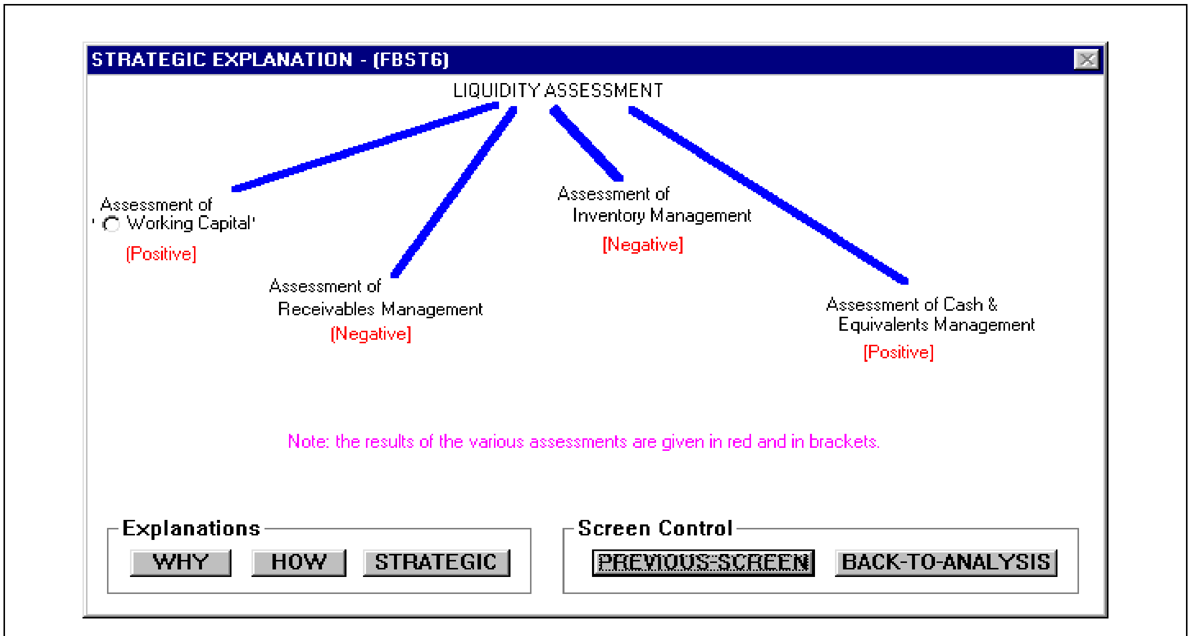
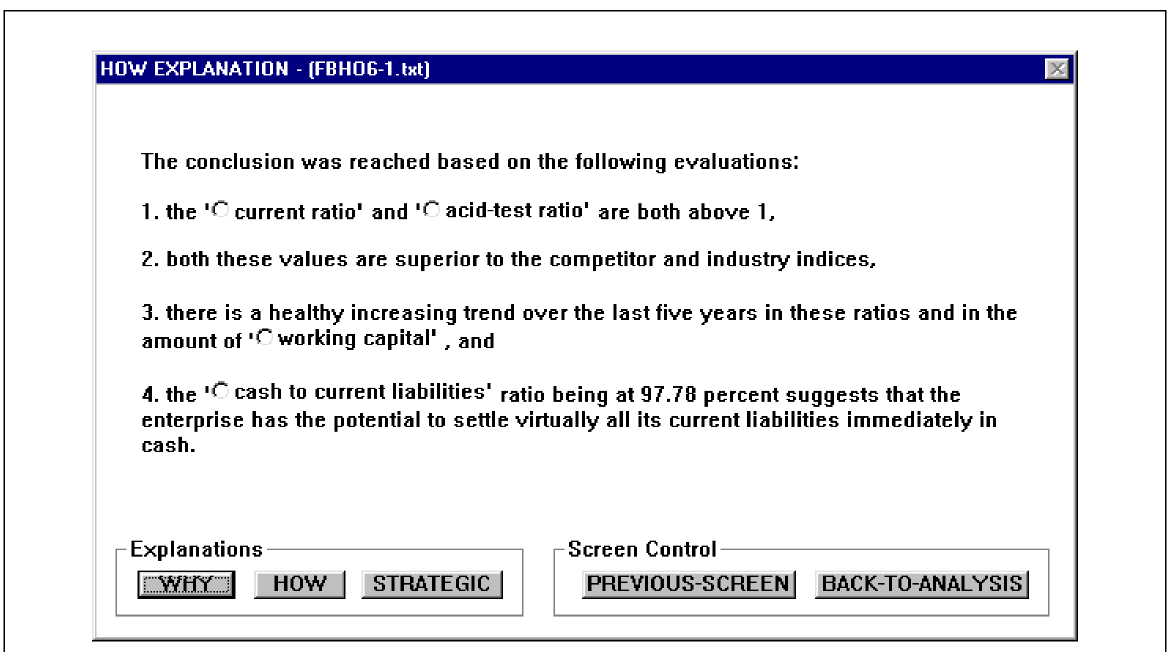
Appendix A



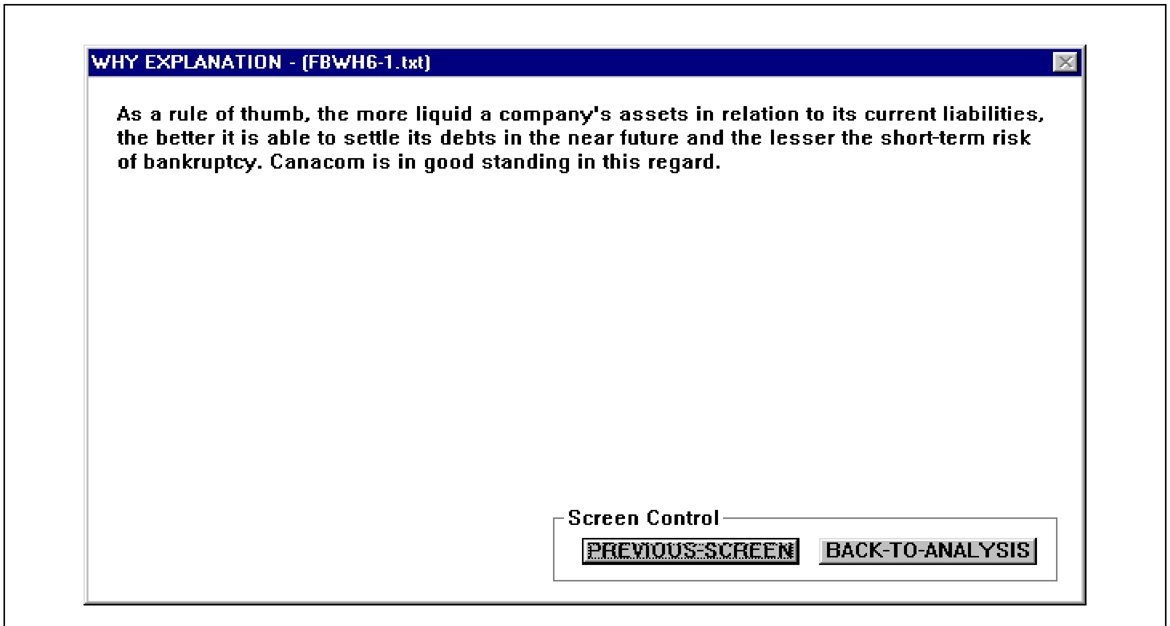
An Example of a Recommendation Screen



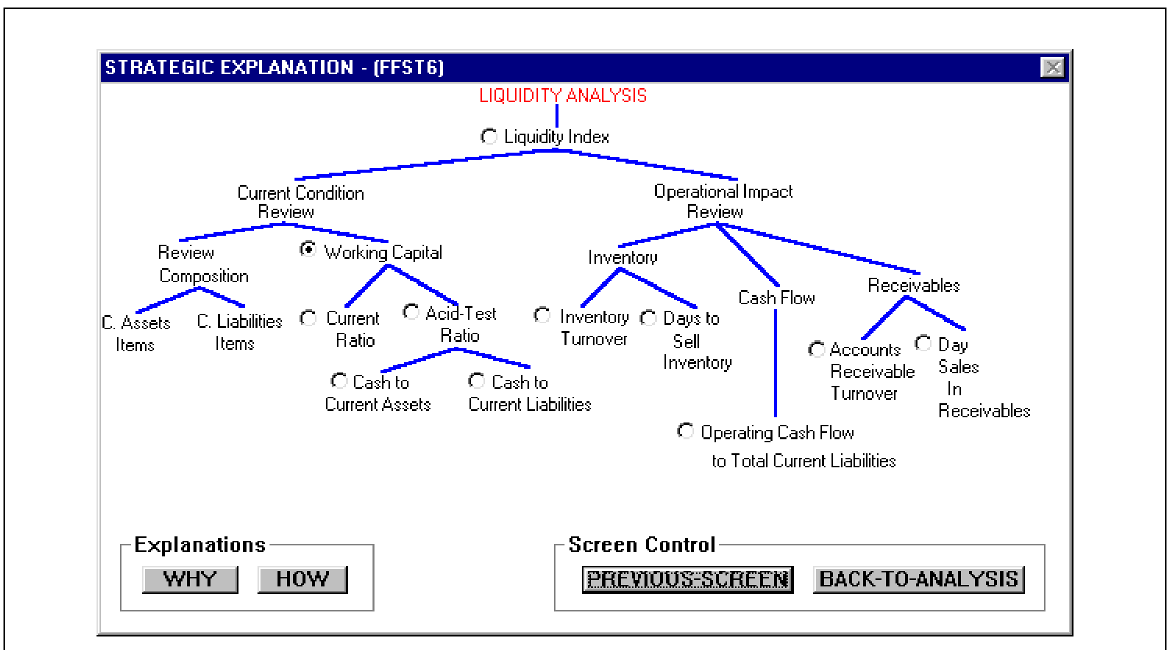
An Example of Reasoning-Trace "Strategic" Explanation



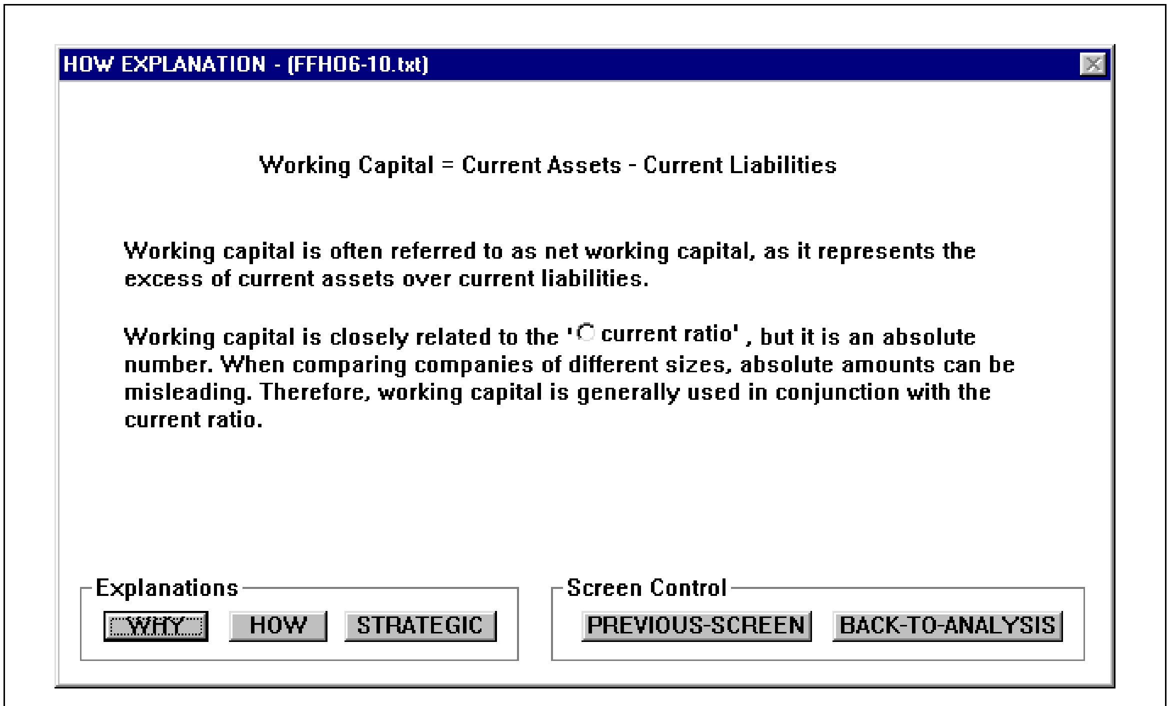
An Example of Reasoning-Trace "How" Explanation



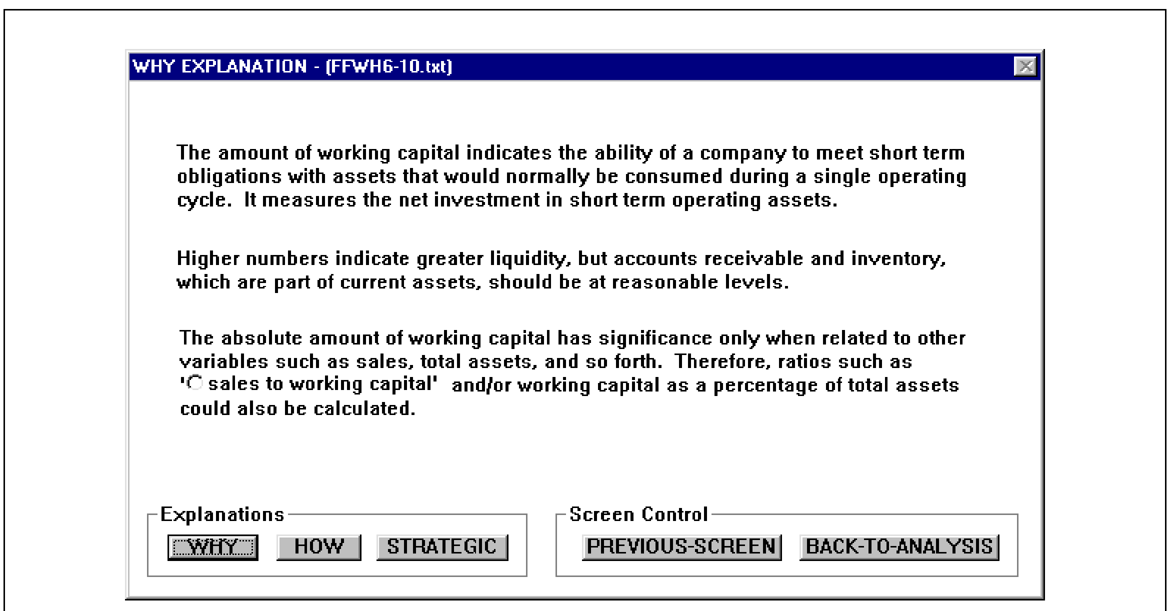
An Example of Reasoning-Trace "Why" Explanation



An Example of Deep "Strategic" Explanation



An Example of Deep "How" Explanations



An Example of Deep "Why" Explanations

Appendix B

1. The use of FINALYZER greatly enhanced the quality of my group's judgments.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

2. Using FINALYZER gave my group more control over the financial analysis task.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

3. Using FINALYZER made the financial analysis task carried out by my group easier to perform.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

4. Using FINALYZER enabled my group to accomplish the financial analysis task more quickly.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

5. Using FINALYZER improved the quality of the analysis my group performed.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

6. Using FINALYZER increased my group's productivity.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

7. Overall, I found FINALYZER useful in helping my group analyze the financial statements.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

8. Using FINALYZER enhanced my group's effectiveness in completing the financial analysis task.

   Strongly disagree: 1 - 2 - 3 - 4 - 5 - 6 - 7 :Strongly agree

Items to Measure Perceived Usefulness of KBS

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