An Empirical Investigation of Explanation Facilities on User Acceptance of System Recommendations

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설명기능이 시스템 결과 수용에 미치는 영향의 실증연구

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Abstract

Providing explanations about recommending actions is one of the most important capabilities of expert systems. In fact, there exist many approaches incorporating this explanation facility into the system. Here we present briefly a new approach to generating these explanations and further attempt to investigate the impact of system explanations on user behaviors toward system-generated recommendations. For this experiment we designed a stock investment decision supporting system which, given a set of market situations, suggests an investment recommendation with explanations about the recommending action. Twenty-nine bank employees evaluated the output of the system in a laboratory setting. The results indicate that explanation facilities can make systems-generated advice more confident to users but cannot increase users' acceptance for the system conclusion.

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1. Introduction

Developing an expert system is a highly knowledge-intensive endeavor. How well an expert system performs heavily depends upon the quality and validity of domain-specific knowledge built into the system. In some domains like stock market, however, domain knowledge is very unstructured and differs from one human expert to another. So it is not easy to acquire domain-specific knowledge directly from human experts in a form of rules [Shaw & Gentry 89 ; Joshi et al. 01]. Instead, expert system developers often take an induction approach in which a set of general rules is constructed from many past examples [Quinlan 86].

In fact, a number of expert systems (ES) in stock investment domain utilized the induction approach [Braun & Chandler 87 ; Lee et al. 93 ; Kim & Han 00]. Though these systems performed quite well in the holdout sample test, they do not offer an explanation facility to users who are unlikely to blindly accept the system conclusion. With an explanation about the recommending action, we believe they would make a more knowledgeable decision.

There exist different types of explanation for expert systems. Ye & Johnson [95] identified three types of ES explanations : Trace, Justification, and Strategy. First of all, one may show a record of the inferential steps taken by an ES to reach a conclusion. Second, an explicit description of the causal argument behind the system conclusion can be provided. Third, one can also suggest a high-level goal structure that determines how the ES proceeds to accomplish a task.

Among these types of explanation, justification type of explanation is most appropriate to induction-based ES. In order to provide a justification type of explanation for ES, one may take a variety of approaches. A complete causal model in a given domain can be utilized if it exists. In a few domains such as physics, medical physiology, and chemical engineering previous research attempted to develop a qualitative causal model and utilized it to generate explanations for the system conclusion[de Kleer & Brown 84 ; Forbus 84]. However, not all domains can afford to have a theoretically driven causal model. Especially it is almost impossible to have a complete causal model in stock investment domain.

A different approach needs to be taken to generate a justification type of explanation for the induction-oriented ES in the stock investment domain. Here we present a new explanation-generating approach based on statistical model building techniques. Our explanation-generating approach starts with a rather incomplete domain model and then refines it using the structural equation model[Hoyle 95 ; Pedhazur 82]. When refining the underlying causal model, we use the original, quantitative data that had been utilized for rule induction. As a result, we can come up with a hypothetical causal model. Such a causal model will be provided along with the system conclusion. Refer to Kim & Park [96] for a more complete description.

However, the more important issue is whether automated explanations will produce the positive impact on the uses of ESs as expected[Ye & Johnson 95]. In this light, we also provide an empirical investigation of the value of ES explanations to users. A laboratory setting was employed to study the impact of the statistical model-oriented explanation on user acceptance of ES-generated advice. Specifically, we were interested in whether such explanation will increase the user confidence of his/her decision and the user acceptance of the system advice.

The next section provides a description of previous research on ES explanation. The following section describes a statistical model building approach for ES explanation. And then research model and research method are described respectively. Finally we provide the results and discuss the findings.

2. Previous research on ES explanation

The presence of a powerful explanation facility is the most critical factor distinguishing expert systems from traditional information systems[Wooley 98]. Experience with expert systems has shown that users demand an explanation for system results and hesitate to accept a solution without explanation [Davis et al. 77, Tatemura 99]. Such an explanation facility has been designed to accomplish a variety of different objectives [Rolston 88]. One most essential objective is to improve the user's confidence of system results. That is, the explanation facility is implemented to convince users that reasoning of the system is appropriate and that its conclusions are reasonable.

In fact, the nature of explanation employed in ES differs widely. Ye & Johnson [95] provided a typology of ES explanations as described below :

- trace (or line of reasoning)
    - it is a record of the inferential steps taken by an ES to reach a conclusion
    - it is usually a reaction to 'how' (how the system obtained a certain conclusion)
    - the system is required to look down through the rules to determine what subgoals were satisfied to achieve the goal.
- justification
    - it is an explicit description of the causal argument or rationale behind each inferential step taken by the ES
    - it requires a deeper understanding of the domain because it must demonstrate that the system conclusion is based on sound reasoning
    - this type of explanation tends to increase the user's confidence in the system and therefore the acceptability of the system
- strategy
    - it is a high-level goal structure that determines how the ES uses its domain knowledge to accomplish a task.
    - It is usually a reaction to 'why' (why the system needs to know)
    - It is to inform the user of the overall plans and methods used to attain the goal
    - It requires knowledge about the problem-solving procedure

They further investigated the impact of these types of explanations on user acceptance of ES-generated advice in a laboratory setting. The results indicate that justification is the most effective type of explanation to bring about changes in user attitudes toward the system. This finding is consistent with Toulmins view that a potentially controversial claim cannot be supported by data alone and a warrant (statements that certify the reasonableness of leaping from data to a claim) will be necessary in order for the claim to be considered acceptable [Toulmin 58 ; Toulmin et al. 84 ; Stranieri & Zeleznikow 99].

Nonetheless, explanation facilities are still underutilized. Johnson & Johnson [93] presented a number of reasons as to why explanation facilities are not more prevalent in present information systems. Designers might not see explanation as useful. Instead they might view explanations as having a high development cost with little added value benefit. And explanation facilities are not presently in a form in which they can be easily incorporated into existing system. Furthermore, we would have to figure out the type of explanations required in different contexts and have to devise an appropriate method to generate and present the explanations.

3. A statistical model building approach for ES explanation

There are two ways of designing an explanation facility to users [Barr & Feigenbaum 82]. First of all, one may design an expert system to represent and explain the reasoning process of the system in a manner that is understandable to the knowledgeable user. Consultation systems as MYCIN and PROSPECTOR require a representational formalism capable of supporting the reasoning and explanation abilities that would closely approximate the conceptual framework of the expert and the user.

Second, one may develop and present the problem-solving expertise of the system in a form that is not at all similar to the expertise. This approach is effective when the method used by a human expert to find solutions is incomplete. For example, in the case of the DENDRAL [Lindsay et al. 80] programs, the generator of chemical-structure candidates employs a procedure for exhaustively producing possible structures based on various graph-theoretic notions. This technique, a major portion of the DENDRAL expertise employed in the procedure, is conceptually opaque and not transparent to the typical user [Barr & Feigenbaum 82]. While the method used by chemists to find solutions for the problems is incomplete, the method employed in the DENDRAL program has been mathematically proved to be complete. One may find a similar approach in the MACSYMA system [Mathlab Group 77].

In other words, the former approach is to explain the reasoning process of the system. In the latter approach, procedures or algorithms rarely used by the human expert are devised for reasoning and explanation of the system. These procedures somewhat opaque to the user can serve as a primary form of explanation due to the correctness and continuing success of these procedures [Barr & Feignbaum 82].

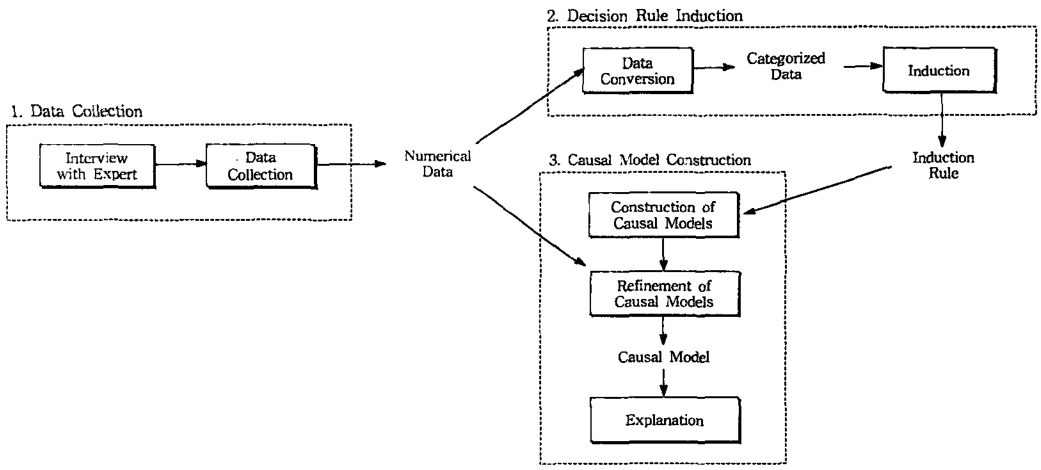
Our approach is similar to the former one in a sense that we seek to acquire a causal model and then present it for explanations. The issue here is how to acquire the causal model from its domain theory. Unfortunately, we cannot afford to find such a causal model easily in stock market domain. Instead, we attempted to build one. It was believed that statistical model building techniques would be applied for this objective. A most representative technique is the well-known structural equation modeling [Hoyle 95 ; Pedhazur 82].

Our explanation-generating approach starts with a rather incomplete causal model and then refines it through application of the structural equation model. When refining the underlying causal model, we use the historical transactions. For a more complete description of our approach, refer to Kim & Park [96]. While (Figure 1) shows the overall process of rule induction and explanation generation, we here mainly describe the explanation-generating process.

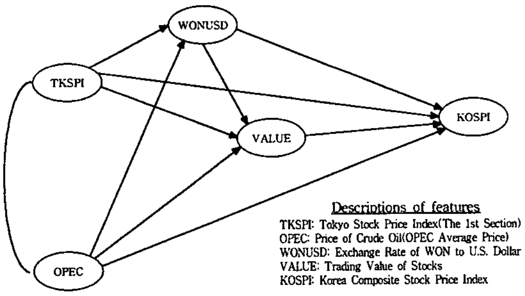
We have taken the following three steps in order to generate explanations for the system conclusion, 1) construction of the underlying model with features used as object descriptors, 2) refinement of the model through application of the structural equation model, and 3) determination of the effect coefficients on the dependent variable.

Initially we start with a hypothetical causal model with features of the rule. This causal model will be constructed with respect to influence groupings. In other words, we build a fully recursive causal model based upon the diagram of influence groupings.

A few assumptions were made in the construction of the model : 1) the causal flow is unidirectional (i.e., the causal models are recursive.), 2) whether each feature is considered as exogenous or endogenous is not predefined ; it depends upon a given model. An example of the hypothetical models is shown in (Figure 2). Please note that this is only an example and there are several other models.



(Figure 1) The overall view of our approach

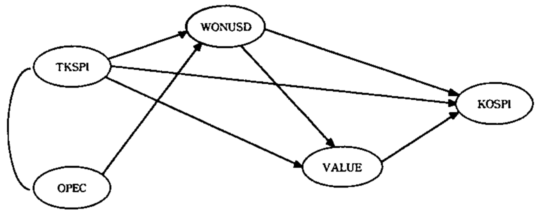


(Figure 2) Example of initial causal model

The next step is to test and refine the underlying casual model using the structural equation modeling approach. In particular, we utilize Foreskin & Sorbom's LISREL [89], a statistical method designed to examine the causality between variables and the validity of the causal model. We first delete causal links, which are determined as insignificant by LISREL and then test the validity of the refined model to come up with a final causal model. An explanation of the decision rule can be generated from the causal model.

The refinement of the model will be explained with the previous example of the causal model. The application of LISREL to the given model indicates that OPEC has no direct effect on KOSPI and VALUE. We use the t-value from which the significance of a causal flow is determined. The deletion of the two causal flows allows us to have a revised model, an over-identified model. (Figure 3) shows the revised model.

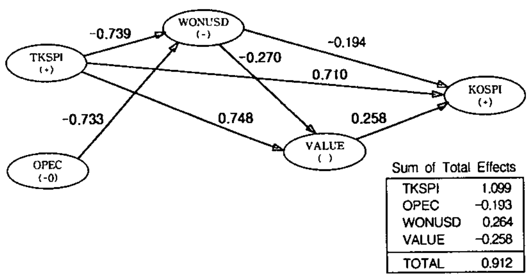
We then check the validity of the revised model through LISREL analysis. As a result, the overall fit of the revised model was evaluated well in terms of chi-square measure, goodness-of-fit indices (GFI), and adjusted goodness-of-fit indices (AGFI). Also the t-values of all causal flows were evaluated as significant.



(Figure 3) Example of model refinement

Finally, we determine the effect coefficients (or the total effects) when determining the expected change in an endogenous variable associated with a unit change in one of its causes. The total effect is computed as its direct effect plus its indirect effects.

(Figure 4) shows the final causal model with effect coefficients. Only direct effects are shown in the figure while the table below shows indirect effects and total effects as well. For instance, the effect coefficient of TKSPI on KOSPI is 1.099, which includes the direct effect



Total Effects of Features on KOSPI

Features	Direct Effects	Indirect Effects	Total Effects
TKSPI	0.710	0.388	1.099
OPEC	*	0.193	0.193
WONUSD	-0.194	-0.070	-0.264
VALUE	0.258	*	0.258

(Figure 4) Example of explanation for induced rule of 0.710 and the indirect effect of 0.388. The sign of this aggregated total effect is checked against the predicted qualitative value of the classification rule. The uniformity of these signs is evaluated as a successful explanation of the classification rule.

4. Research Model and Hypotheses

Expert system literature has shown that users demand an explanation for system results and tend not to accept without an explanation [Davis et al. 77]. We, however, hardly find an empirical research of validating the effect of explanation produced by an expert system. Carroll & McKendree [87] have identified the lack of empirical research as a key reason for the limited impact of expert systems technology. Johnson & Johnson [93] suggested a number of reasons as to why an explanation facility is not a ubiquitous feature of current information systems.

Ye & Johnson [95] attempted an empirical investigation of ES explanation facilities. Their main concern was to examine the impact of ES explanations on users' acceptance of ES-developed conclusions and to identify the type of explanation that is most effective in producing such an impact. For this study, they conducted a laboratory experiment with a diagnostic expert system performing auditing tasks. The results indicate that explanations can have a positive impact on user acceptance of an expert system and justification type of explanation is the most effective in making the system's conclusion more acceptable.

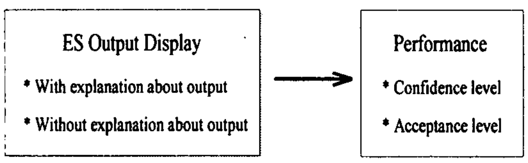
From a pool of interface design research, we may gain an understanding of system requirements. Effective design of interfaces requires an empirical understanding of the relationships between user expertise, explanation presentation format, problem characteristics, and facilities of information system. Though this realization has facilitated a considerable number of researches with respect to traditional kinds of information systems such as management information system and decision support systems [Zmud 79, DeSanctis 84, Sharda et al. 88], only a few research were achieved in the context of expert system.

Considering such a divergence, Lamberti & Wallace [90] evaluated intelligent interface requirements for knowledge presentation in an expert system. They emphasized the requirements for knowledge presentation and the cognitive compatibility between the user and the expert system. Their findings indicate that procedurally formatted lines-of-reasoning seem to offer an advantage in explicitly presenting knowledge about processes used in strategies for problem solution and high-skill employees' confidence rating is better than those of low-skill employees for system recommendations, lines-of-reasoning, and decisions. They also found that users more confident about system recommendation, lines-of-reasoning, and final decision took less time in making a final decision for the problem solution. Though their research found many interesting points about interface design requirements, the question of explanation facility's effectiveness is not answered.

Somewhat relevant research in database

interfaces was also found. Suh & Perkins [94] empirically examined the effects of feedback echo in a restricted natural language database interface. According to this study, the feedback echo of Intellect (a commercial database system) did not improve the performance of novice users in terms of error recovery rate, confidence, and communication errors. These unexpected results may have come from the given system's inadequate functionality of feedback echo.

This study attempts to investigate the effects of explanation in expert system (ES). Our research question can be stated like "Is there significant difference in user performance about the system conclusion between ES users with explanation and ES users without explanation?" We understood the user performance (or behavior) about the system conclusion as consisting of two different notions : confidence and acceptance. First of all, the confidence is concerned with the degree of user's belief about his or her decision. The acceptance corresponds to the degree of user acceptance of ES advice. The research model of this study is illustrated in (Figure 5).



(Figure 5) The Research Model

This study examines two specific hypotheses related to the research question. First of all, the system conclusion with relevant explanations would enhance user's confidence about his or her decision. The IE subjects receive from the system a graphical description indicating causal relationships among user-supplied variables. This description resembling the problem-solving expertise of the system is generated to convince users that the system's reasoning is appropriate and that its conclusions are reasonable [Barr & Feigenbaum 82, Swartout 83]. If this description can increase an understanding of the system's reasoning, then the IE subjects will be more confident about their decision than the NE subjects. Hence, the null hypothesis is stated like :

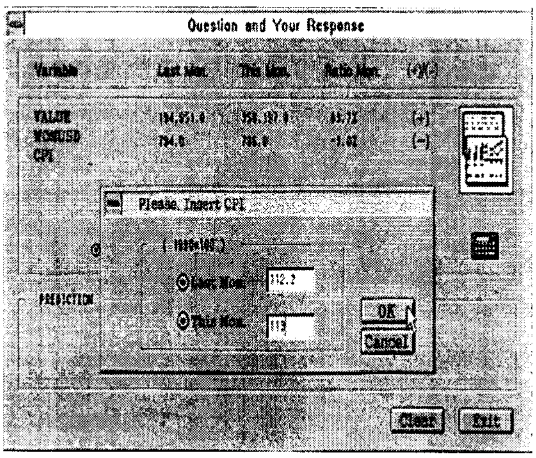
H1 : There is no significant difference between the including-explanation (IE) group and the non-explanation (NE) group in terms of user confidence levels.

Second, good explanations may be working in such a way that users tend to accept the system conclusion and follow recommendations suggested by the system. Rolston [88] found that if there is a chance of the system producing incorrect results, then the user could not blindly accept system results. In particular, for the user of the system who needs clarification or reassurance about the system's output, the importance of accompanying explanation facilities increases. The more understandable the system's output is to the user, the more the user tends to follow the system's conclusion. Accordingly, the null hypothesis of the second is stated like :

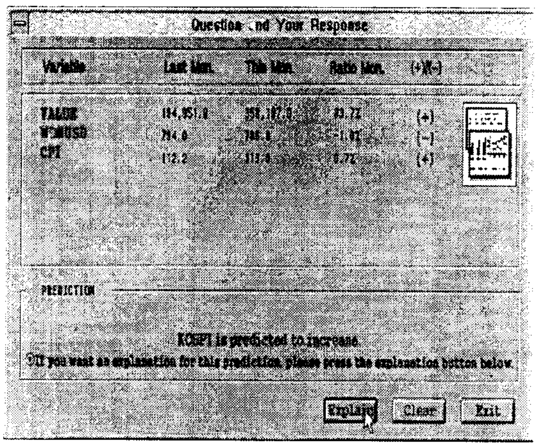
H2 : There is no significant difference between the IE group and the NE group subjects in terms of user acceptance of the system conclusion.

5. Method

We employed a posttest-only control group design in order to examine the above hypotheses. In other words, subjects are randomly assigned to one of the two groups, with and without explanation.



(Figure 6) The screen for acquiring subjects input.



(Figure 7) The screen for displaying the systems conclusion

The system employed in the present experiment was implemented in Excel package for Microsoft Windows. The system was designed to accept numerical values for a given set of variables from user and to generate a direction of stock price movement, up or down. (Figure 6) and (Figure 7) show the input process by the user and the conclusion made by the system.

5.1 Subjects

Twenty-nine people working at the computing center of a major commercial bank participated in the study. Information systems workers were selected because their computing skill allowed us to directly proceed to the experiment without a particular training session prior to the experimental study. Their age ranges from 20s to 30s. Even though they may have investment experience personally, their current job is not directly related to stock investment. Each employee was randomly assigned to the IE group or NE group.

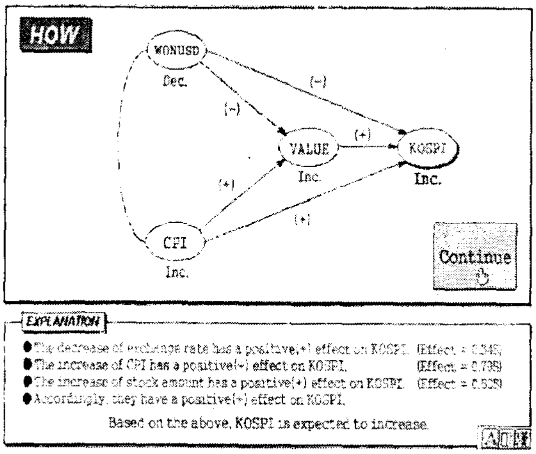
The sample size of 29 was not large. We here have to admit that we had a limitation in increasing the number of sample sizes due to laboratory-specific requirements. First of all, the number of personal computers available in the computer lab limited us. And, we thought a significant level of computer experience was needed for each subject, so we had to use information system workers. So the number of workers in the information systems department also limited us. Since our study was just an explorative study in investigating the effect of explanation facility, the size of 29 subjects would suffice for this objective. But, a care must be taken in understanding the result of this experiment.

5.2 Procedure

Each subject was given four cases. For each case, the subject was assumed to have a portfolio of 1M(million) won in cash and 1M-valued stocks.

Each case was made up by us. It means what variables would be used at each case and what values for each of these variables would be inserted was fixed prior to the experimentation.

Each subject was required to enter a set of numerical values for the given stock market variables of each case into the terminal. The experimenter provided these values. Then the system responded with a stock market prediction ('increase' or 'decrease') with a corresponding explanation. For the NE group, the explanation facility of the system was turned off during experiment. (Figure 8) shows an example of explanations about the system conclusion. This is just one of the four cases. For the other cases other explanation models were used for their explanation.



(Figure 8) The screen of the system explanation

Then we asked each subject to answer on two questions. First of all, the subject was asked to determine his or her own investment decision and to select one of the following five options :

(1) Sell all stocks
(2) Sell half of stocks
(3) No change in portfolio
(4) Invest half of the cash in buying more stocks
(5) Invest all of the cash in buying more stocks

The subject was asked to measure the level of confidence assigned to his or her decision and to choose one of the five different scales from 0%, 25%, 50%, 75%, and 100%.

5.3 Measurement

As shown above, the level of confidence and acceptance of subjects were measured using a single question. It was quite possible to ask more than one question in order to identify the level of accepting system results. For instance, whether to understand the result, how much credit to give to the result, and whether to follow the system conclusion are some possible questions. However, in stock investment decision designed for a universal and clear goal, we think that the one question with 5 different optional answers would work for this objective. That is, having followed the investment decision directed by the system covers understanding and believing as well.

While subjects' response about confidence is used as it is, we need a conversion to get the level of acceptance. If the system's output were not meaningful at all to the user, the user would maintain his or her portfolio. Therefore, for cases in which the system responded with a prediction of 'increase', the level of acceptance was calculated according to the following formula :

Acceptance level = subject's response about acceptance - 3.

For instance, if the subject responded with 4, the acceptance level will be 1. With the response of 1, the acceptance level will be -2.

Accordingly, for cases with a prediction of 'decrease', the level of acceptance was calculated according to the following formula :

Acceptance level = 3 - subject's response about acceptance.

6. Results and Discussion

The results are summarized in <Table 1>. The independent samples t-test is used to analyze differences between means of the two groups.

The result shows that the IE group (3.48) had a higher level of confidence than the NE group (3.21). It was a significant difference. The explanation generated in the system was able to increase a user's level of confidence. This result supports the increased confidence of the explanation facility, which has been hypothesized in ES literatures.

〈Table 1〉 Summary of Results

Measurement	Mean		t	p	Related
	IE	NE			Hypothesis
Confidence Level	3.480 (.338)	3.210 (.275)	2.36	.026	H1
Acceptance Level	1.000 (0.172)	1.012 (0.124)	-.08	.94	H2

However, there was no significant difference between the two groups in terms of acceptance level. Furthermore, the mean score for the IE group was smaller than that for the NE group. One possible reason for the unexpected result is that ES users may not really anticipate the system's advice that they would blindly follow. They may just view ES as a decision aid from which they determine how much reasonable their problem-solving expertise is.

Owing to this indifferent acceptance of the system conclusion we may have to ask ourselves for a second thought about the effectiveness of the ES explanation facility. As a matter of fact, there have been previous studies in which users question the utility of having an explanation facility or ignore the explanation facilities [Hart & Wyatt 90 ; Slatter et al. 88].

7. Conclusions

Our study described briefly an explanation-generating approach using a statistical model-building technique. An empirical investigation of such explanation-generating approach was described as well. The result indicates that the explanation facility enhanced user's confidence about his or her decision. It, however, did hardly increase user's acceptance of the system output. The particular type of explanation facility implemented in our system was not effective enough to increase user's acceptance level. We believe that further research is needed to devise a more effective explanation facility for the induction-based expert system.

The fact that ES has the effect of confidence enhancement but not the effect of acceptance leads us to speculate that decision makers use ES for simply checking their problem-solving expertise against the ES-generating output.

Care must be placed in generalization of the results from this study since this experiment contains a few limitations. The sample size of 29 must be too small to elicit meaningful outcomes. We employed the use of office worker subjects in order to evade problems related to the use of student subjects in a laboratory setting. And, this experience focused on a single problem domain. The generalizability of the results would increase if this statistical model-building approach were attempted for other domain problems as well.

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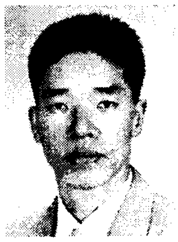
■ 저자소개

김 성 근

공동저자 김성근은 미국 New York University에서 Information Systems 박사학위를 취득하였다. 동 대학에서 전임강사를 거친 후, 한국산업투자자문(주)의 전문위원과 고문을 역임하였다. 미국 방성 산하 전자상거래센터에서 연구원을 역임하였으며, 현재 중앙대학교 경영학과 교수와 중앙대학교 전산원장으로 근무하고 있다. 주요관심분야는 정보계획수립, 데이타베이스응용, 지능형 정보기술 활용 등이다.



강 현 구

공동저자 강현구는 91년도 서울산업대학교에서 전자계산학 전공으로 학사, 96년도 중앙대학교에서 경영정보시스템으로 경영학석사를 취득했다. 현재 주택은행 정보기획팀에서 근무하고 있다. 주요관심분야는 지능형 정보시스템, 멀티미디어, 객체지향 등이다.