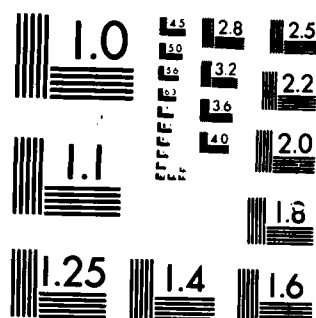


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**COGNITIVE FACTORS IN USER/EXPERT
SYSTEM INTERACTION**

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significantly decreases user/expert system problem solving performance. Users not possessing an accurate mental model reach higher performance when utilizing cognitive consistent procedures. The practical implications of this theory are briefly discussed.

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INTRODUCTION

In the past decade, a decision aiding technology has emerged from the discipline of artificial intelligence that has the potential for greatly improving the decision speed and quality of decision makers information analysis and problem solving process. Specifically, rule-based expert systems have been developed which exhibit domain specific problem solving behavior that is comparable in quality to that shown by human experts. From a cognitive human factors perspective, it has been argued and generally accepted that a prerequisite for effective user/expert system interaction is a high degree of consistency between the user's and expert system's domain knowledge. That is, the expert systems should solve the problem in the same manner, applying the same rules, that a human expert does.

In this paper, we argue that this argument is incorrect and furthermore that for many contexts, significant consistency in the user and expert systems problem solving approach is actually undesirable. Three experiments providing empirical support for this hypothesis are presented.

Historically most expert systems have been developed to operate in time-relaxed consultation environments where the system requests from the user a substantial amount of information about the problem at hand. Examples of fully developed systems of this type are MYCIN (Shortliffe, 1976) which diagnoses bacterial infections and recommends antibiotic therapy, and PROSPECTOR (Duda, et al., 1979) which evaluates geological mineral sites for potential deposits. Recently, however, expert system technology has focused on the use of expert

systems as intelligent interfaces between a user and a larger complex information processing system. These expert interface systems use the same rule-base program architecture found in consultation systems, however, they automatically acquire data from an external source rather than requiring data information from the user. Thus the primary function of the expert interface system is to enhance a user's ability to utilize an external data source, often a large system that operates independently of the expert interface. Proposed applications of expert interface systems include centralized sensor integration and display control, and real time C² decision making support (Walker and Lehner, 1985).

From a human factors perspective, there are some key aspects of expert interface systems that make them very different from expert consultation systems. First, consultation systems tend to address problem domains with a well-established, well-documented, and static knowledge base. Expert interface systems on the other hand, tend to involve ill-specified knowledge bases, where human experts differ considerably in their opinions. Second, the time constraints on the decision processes of interface systems is typically shorter than is the case with consultation systems. Third, consultation systems are stand alone, requiring the user to enter all problem specific data. As a result, consultation system users must have sufficient domain expertise to answer the system queries. In contrast, expert interface systems are usually embedded within a larger 'background' system. Thus, users are not a priori familiar with the specifics of the problem being addressed. Indeed, the user may not even know a problem exists until the expert system has already analyzed data obtained from

the background system and generated its conclusions and recommendations. The user, therefore, will typically find it necessary to examine the data and rules that led to the system conclusions.

Given the above types of expert systems, the user/expert system interaction can be viewed as a situation where two problem solvers are trying to cooperatively solve a common decision problem despite the fact that these two experts may use different decision process, heuristics and data to solve the common problem. Two cognitive factors seem particularly relevant when examining this interaction:

- (1) the degree to which the user and expert system's problem solving processes utilize similar domain and problem specific knowledge, and
- (2) the user's conceptual understanding of the basic principle of the system's problem solving processes, i.e., the user's mental model. It is postulated that in a user and expert system problem solving situation, performance is dependent on both of these two variables, and that there is a strong interaction between them in their impact on performance.

Specifically, we hypothesize that a good mental model of expert system processing would facilitate user understanding of system recommendations and explanations even if the system's problem solving approach is substantially different from the user's. Furthermore, when the user and expert system are viewed as two interacting production systems, the potential improvement of cooperative problem solving over individual user or system problem solving increases proportionately as the degree of overlap between the user's and the expert system's problem solving processes decreases, i.e., with decreasing cognitive consistency. However, in order to realize this

potential, the user must be able to incorporate the system's cognitions into his or her own reasoning about the problem. Thus it is predicted that when a user possesses an accurate mental model, cognitive inconsistency should generally result in better performance than problem solving involving a high level of cognitive consistency. If the user, on the other hand, does not have a good mental model of the expert system's processing, the conventional wisdom, suggesting that performance improves as the overlap between the user's and system's cognitions increase, may be correct. The following three experiments test these general hypotheses.

EXPERIMENT 1

Method

In this experiment, both the subjects and expert system had isomorphic decision rules (i.e., they would provide the same solution), however, there was inconsistency in the data sets. The expert system had access to data which the subjects initially did not have, while the data the subjects did possess was more accurate than the expert system's data. Under these conditions, subjects were required to interact with the system to obtain all relevant data, however, the expert system did not necessarily generate the correct solutions.

Subjects. Thirty-two (16 male and 16 female) undergraduate students from the Catholic University of America served as volunteer subjects in this study. The mean age was 19.3 years with a range of

17-22 years. None of the subjects had previous experience with rule-based systems or computer-aided problem solving tasks.

Materials. The framework used for development of the intelligent interface was ERS, Embedded Rule Based System (Barth, 1984), which is in many respects similar to the well known PROSPECTOR inference engine (Duda, et al., 1979). The ERS system consists of an inference engine, rule base parser, and language for representing rules. Rules in a test file are parsed and compiled into internal data structures during run-time initialization. The inference engine then uses these data structures to drive the system's decision making process. This process may involve gathering evidence from the user, as is usually done in expert consultation systems, or from a set of primitives supplied for a particular application, or both. As sufficient evidence is gathered, conclusions or advice is reported in the form of the degree of belief in the top level, goal hypotheses that were defined in the rule base. The system continues gathering evidence and reporting advice, until no more evidence remains to be gathered, or the user issues a quit command. Written in Pascal, ERS was developed on a VAX-11/780 under the UNIX operating system, version 4.1 bsd. and has been installed on an IBM PC with 128 bytes of memory, under the UCSD P-System.

For this study, a simplified version of ERS was implemented on an Apple IIe microcomputer with 64 bytes of memory. The rule base representing the testbed domain consisted of an inference network containing 63 nodes, 5 goal hypotheses, 39 rules, and 109 links between nodes. This system was employed for all three experiments.

Experimental Design. A 2 x 2 factorial design was used to create

the experimental conditions. The two independent variables were (1) cognitive consistency and (2) mental model. The two levels of cognitive consistency were created by the nature of the problem solving style used by the subject. In each problem, the expert system operated in a goal-driven, backward-chaining manner through the rule base to evaluate goals. High cognitive consistency was defined when the user was taught to problem solve in a similar goal-driven, backward-chaining manner. Low cognitive consistency occurred when the user problem solved in an almost opposite, data-driven, forward-chaining process. The application of both procedures resulted in identical final solutions for all data possibilities.

The two levels of the second independent variable, mental model, were (1) accurate mental model and (2) no mental model. Subjects in the accurate mental model condition received as part of their instructions a written description of an inference network. This section described the structure of a general inference network, explained how the expert system identified goals, intermediate hypothesis, and data items, and chained up and down the network to obtain degree of certainty values for each goal. Included in this section was a pictorial display of an inference net and a simple example of its operation. By working through this section, the user developed a mental model of how the expert system solved problems.

Testbed Domain. The experimental domain for all three experiments was a simulated stock market setting in which five different types of securities fluctuated in value during the testing sessions. The increase or decrease in security values was influenced by two types of data: (1) general market conditions, and (2) specific trading

activities. Market conditions concerned the degree to which the general market state could be identified as "bear," "mixed," or "bull." Trading activities described the volumes of buying/selling during a hypothetical time frame, e.g., "Blue Chip securities were sold by 5000 shares in two weeks."

Task problems were constructed by creating patterns of specific market conditions and trading activities and defining the resultant security value fluctuations. For each possible pattern of data combinations there was exactly one of the five securities whose value increased the highest. Thus, for each task problem there was one optimum security that should be recommended for purchase.

Expert System. The expert system, used in the three experiments, included an inference network in which each of the five securities was set as a goal. The experimenter provided the system with access to data concerning previous market conditions (e.g. "bear"), current market conditions (e.g., "mixed"), and the volumes and direction that each security is currently being traded. The system utilized backward-chaining procedures to validate the degree of belief in each of the lowest-level data nodes, assess value to the intermediate hypotheses, and in turn estimate the degree to which each of the five securities should be recommended for purchase. At this point the system displayed the five securities as rank-ordered (greatest to poorest) recommendations for purchase.

Procedure. After reading a description of the experiment and signing a consent form, subjects received the instruction booklet pertaining to their particular mental model/cognitive consistency group condition. These instructions specified the objectives,

procedures, and requirements of the problem solving task. Each set of instructions previously defined the level of mental model and type of problem solving procedures to be implemented.

Subjects were seated at a large table directly in front of the expert system with ample space to arrange their individual problem solving sheets. Upon completion of the experimental booklet, subjects received three test problems to practice use of their own procedures. The type of data presented to the subject was of the same nature, i.e., market conditions and trading activities, that the expert system utilized. Competent use of the appropriate styles of procedures, either (1) cognitive consistent or rule-driven, backward chaining, or (2) cognitive inconsistent or data-driven, forward chaining, was reached by all participants.

At this time subjects received practice interacting with the expert system. After viewing the system's prioritized list of security recommendations, users practiced querying the system for its decision rationale. In other words, the user saw what the expert system recommended for a specific problem and sought to determine "how" and/or "why" this particular recommendation was reached. Through the use of a node description command, initiated by the entering of a "d," carriage return, and specification of the node name to be examined, users were able to examine important components of the systems logic and reasoning. Successful interaction with the system involved the specification of several successive node description commands to reach meaningful information, e.g., the degree of certainty of the systems lowest level data items.

The experimental process tested subjects individually for six

separate problems. A time constraint of 150 seconds was imposed upon each task. Pilot studies demonstrated this time allowance as adequate for proficient interaction with the system and use of individual problem solving procedures.

Each of the problem solving tasks proceeded as follows. Seated in front of the expert interface system with individual problem solving sheets within easy reach, a subject viewed the system's rank ordered list of security recommendations for the current problem. The experimenter handed the subject written data concerning "previous market" and "current market" estimations. At this point the subject could allocate time to either querying the system with the "d" command, utilizing the individual problem solving sheets, or a combination of both. After 180 seconds, the subject viewed the system's recommendations a final time and terminated the problem solving session. The subject recorded on an answer sheet by simply checking off the one or two securities most recommended and by writing a few sentences describing why.

At the completion of six such problems, subjects completed a brief questionnaire assessing reaction to the problem solving experience and were adequately debriefed.

Performance Measures. For each of the six problem solving tasks, one of the five securities had been evaluated as the optimal recommendation during task construction. This benchmark solution was reached by utilizing problem solving procedures applied to the complete data set. It should be noted that both types of procedures, forward-chaining and backward chaining, reached the same conclusions given the same data. Thus, for each of the six problems a benchmark

solution was constructed as a comparison for the subjects' responses.

The major performance measurement was the number of times a subject's response matched the predetermined optimal one. Individual scores could range from 0, none of the problems correct, to 6, all of the solutions matched with the optimal ones.

A second performance measure was the 10-item subjective questionnaire. Subjects indicated on a 10-point scale from 0 ("very strongly disagree") to 10 ("very strongly agree") their agreement with statements addressing (1) the understanding of the expert system's operating procedures, (2) the ease of system use, (3) the confidence of final user decisions, and (4), the adequacy of the time allotment.

Finally, the number of user queries to the expert interface system were recorded. These "d" commands were noted for each subject over each of the six problems.

Results

The principle issue in this experiment was the combined effect of mental model and cognitive consistency on subjects problem solving with an expert system. The data set was subjected to a 2 x 2 analysis of variance procedure investigating the main effect of each of the independent variables as well as the interaction between them. The strong main effect of mental model, $F(1,28) = 11.15$, $p = .00214$, demonstrated that an effective understanding of the system's operating procedures facilitated cooperative problem solving quality. As predicted, a main effect for cognitive consistency did not occur, $F(1,28) = 0.0$. The presence of a significant interaction between mental model and cognitive consistency, $F(1,28) = 8.2$, $p = .0079$, supports our central hypothesis and theoretical basis for user/system

problem solving.

A graphical presentation of subject correct responses as a percentage of total problems is depicted in Figure 1. The mental model/cognitive consistency interaction is easily observable. Individual comparisons confirmed several hypotheses. For those possessing an accurate mental model, inconsistent (forward-chaining) procedures led to a significantly greater performance, than consistent (backward-chaining) procedures $t(14) = 2.17, p < .05$. For users without an accurate mental model performance improved when consistent (backward-chaining) procedures were followed, although this difference failed to reach significance, $t(14) = 1.90, p = .079$. When evaluating the two groups implementing inconsistent procedures, subjects possessing an accurate mental model performed significantly better, $t(14) = 4.13, p < .01$.

Further data analysis was performed by evaluating subjects responses to the 10-item subjective questionnaire. Users receiving accurate mental models reported greater "understanding of the system's operating procedures," means of 5.7 and 5.7 (cognitive inconsistent and cognitive consistent respectively) than those without an accurate mental model, means of 3.4 and 3.8 respectively. Reports of "ease of system use" followed the general interaction pattern, the means being 7.9, 6.7, 6.8, and 5.8. "Confidence of final user decisions" followed the same pattern with means of 7.9, 6.7, 6.8, and 5.8. The "adequacy of the time allotment" revealed the lowest performing group of no mental model/cognitive inconsistent to be most time pressured, mean of 2.8, compared to the other three groups with means of 4.8, 5.5, and 4.4 respectively.

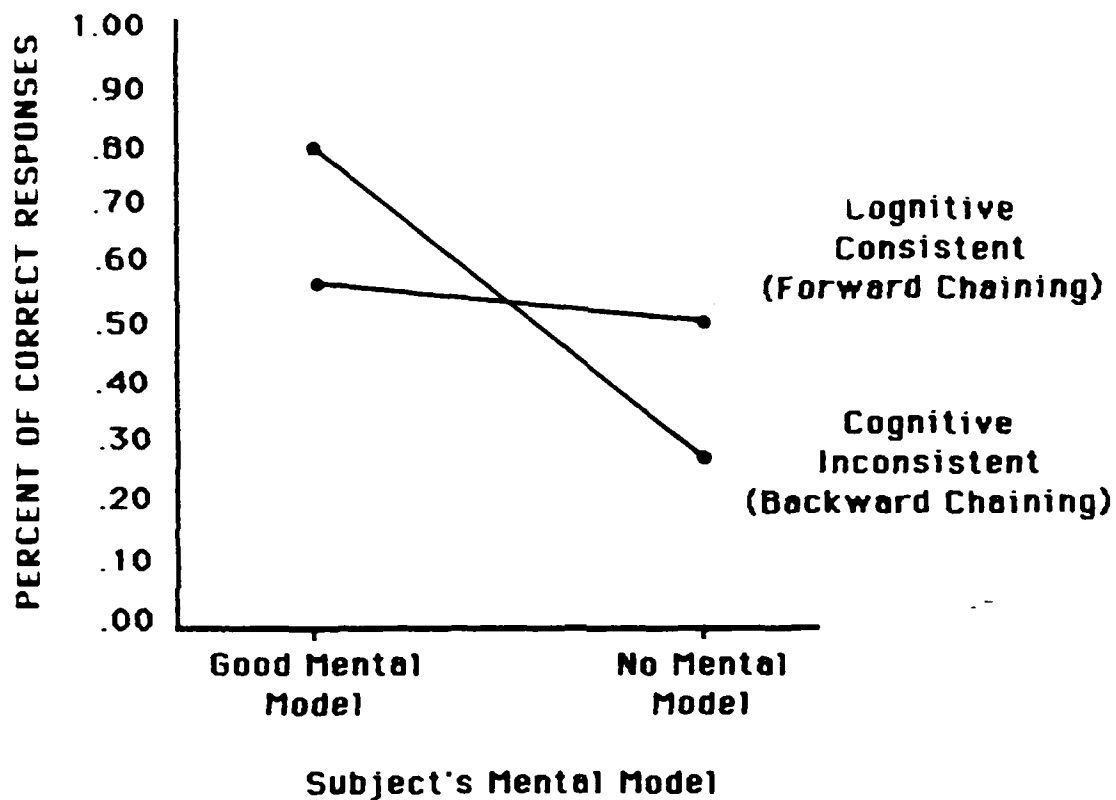


FIGURE 1
PERFORMANCE AS PERCENTAGE OF OPTIMAL RESPONSES BY GROUP
(Experiment 1)

The final performance measure of the number of user queries during user/system interaction revealed no differences across the four conditions, the means being 4.9, 5.2, 5.27, and 5.01 respectively.

EXPERIMENT 2

Method

In Experiment 1, there was a 60% difference in performance between the good and no mental model groups under the cognitive inconsistent condition. One hypothesis to account for this difference is that good mental model subjects were much more facile in manipulating the expert system than the no mental model subjects. As a result they were able to manipulate the system to get access to all relevant data, while the no mental model subjects were not able to do this. Experiment 2 tested this hypothesis. Specifically, this experiment examined whether users utilizing forward-chaining (cognitive inconsistent) procedures with no mental model of the expert system's problem solving processes could significantly improve their problem solving performance if given direct access to the system's data. It was predicted that if users with no mental model using inconsistent procedures could obtain an immediate display of all relevant data the system had available, their performance would not significantly differ from users with a good mental model using inconsistent procedures.

Subjects. Sixteen (17 male and 9 female) undergraduate students from the George Mason University served as subjects in this study.

The mean age was 18.5 years with a range of 17-21 years. None of the subjects had previous experience with rule-based systems or computer-aided problem solving tasks.

Experimental Design. A between subjects design was used to examine one independent variable, mental model, with respect to low cognitive consistency. The two levels of mental model, were (1) accurate mental model and (2) no mental model. Subjects in the accurate mental model condition received as part of their instructions a written description of an inference network. This was the same description as that given to subjects in Experiment 1. The subjects in the no mental model condition were not given this description of the system's inference network, however, they could access the system's data by using a data description command as described in the Procedure section.

As in Experiment 1, low cognitive consistency was created in all subjects by teaching the user to problem solve in a data-driven forward-chaining process.

Procedure. The procedure was identical to that of Experiment 1, with two exceptions. The first being that users with a good mental model and inconsistent procedures were compared only to users with no mental model and inconsistent procedures. Thus, two groups of subjects (rather than four groups as in Experiment 1) were examined.

The second difference between Experiment 1 and Experiment 2 was that a data description command was employed in Experiment 2. Users with no mental model were able to examine, through the use of a data description command, the system's actual data (i.e., the market conditions and trading activities) that it used to reach its

conclusions. This command was initiated by entering a "w", carriage return and specification of the data to be examined.

Performance Measures. The performance measures were identical to those of Experiment 1 with the exception that the number of user queries to the expert interface system were not recorded.

Results

This experiment examined the performance of users without an accurate mental model and with direct access to the system's data (i.e., the data description command) with the performance of users with an accurate mental model and no direct access to the system's data. The data set was subjected to a t test (one factor analysis of variance) procedure. Results demonstrated that users with direct access to the system's data but without an accurate mental model did not significantly differ from users without direct access to the system's data but with a good mental model, $F(1,14) = .78, p > .05$. A graphical presentation of subjects' correct responses as a percentage of total problems is depicted in Figure 2.

Further data analysis was performed by evaluating subjects' responses to the 10-item subjective questionnaire. As expected, users receiving accurate mental models reported greater "understanding of the system's operating procedures" than those without an accurate mental model (means of 6.3 and 3.7 respectively). Users with accurate mental models also reported greater "confidence of their final decisions" than those users without an accurate mental model (means of 6.4 and 3.5 respectively). The "adequacy of the time allotment" followed the same pattern with means of 5.6 and 3.2. However, "ease of system use" was found to be greater in users with no mental model

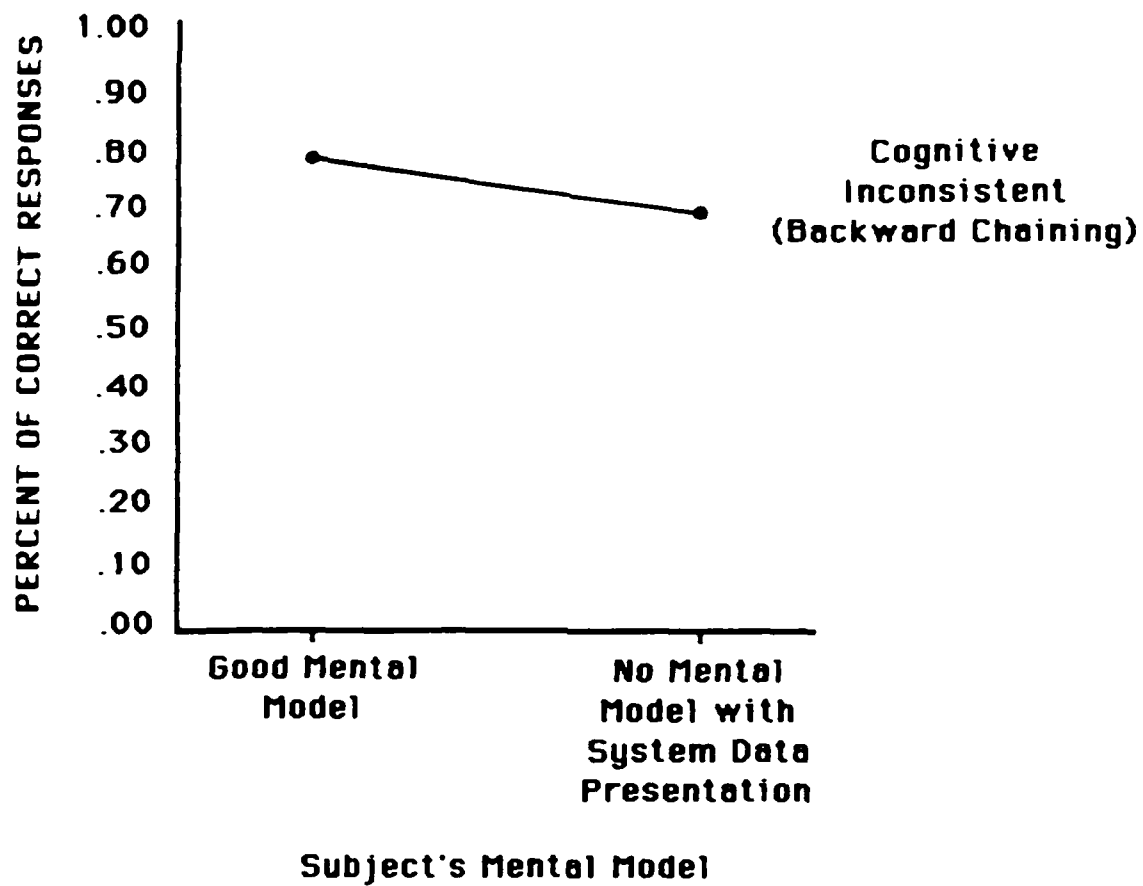


FIGURE 2
PERFORMANCE AS PERCENTAGE OF OPTIMAL RESPONSES BY GROUP
(Experiment 2)

than in users with an accurate mental model (means of 5.2 and 4.8 respectively). This last finding suggests that if a user with no mental model has the capability to access the system's data directly, he or she will find the system much easier to use.

EXPERIMENT 3

Method

In the previous two experiments, subjects had little need to actually trace the expert system's reasoning to obtain assistance in problem solving, rather they simply used a sequence of commands to reach the system's data. Consequently, it was not clear the extent to which a good mental model helped subjects actually understand how the system generated a recommendation. This third experiment addressed this latter issue. In particular, we examined the effect a user's mental model has on performance when the user is required to examine and identify inconsistencies between the system's rule-base and the user's problem solving procedures. It was predicted that a good mental model would allow the user to effectively chain up and down through the system's rule-base, whereas users with no mental model would in effect, become "lost" unless they were using the same problem solving procedures (i.e., backward chaining) as the system.

Subjects. Thirty-two (14 male and 18 female) undergraduate students from the Lord Fairfax Community College served as volunteer subjects in this study. The mean age was 19.6 years with a range of 17-30 years. None of the subjects had previous experience with

rule-based systems or computer-aided problem solving tasks.

Experimental Design. The experimental design was identical to that of Experiment 1.

Procedure. The procedure was identical to that of Experiment 1 with the exception that subjects received a statement indicating the system's solution if it was free of error in addition to problem solving sheets that led to solutions inconsistent with the rule-base employed by the system. The system's solution if it was free of error was identical to that obtained using the problem solving sheets. Thus, the system and the problem sheets resulted in two different solutions. Subjects were told that the system contained an error in the way it solved each problem. Subjects were required to identify the inconsistency or difference between their problem solving sheets (or the problem solving logic used by the system if it was free of error) and the procedures (or problem solving logic) utilized by the expert system (e.g., situation A on Sheet 1 was interchanged with situation C on Sheet 3).

Performance Measures. The major performance measure was the number of times a subject correctly identified an inconsistency between the system's solution and the solution provided by the problem solving sheets. All other performance measures were identical to those utilized in Experiment 1.

Results

The principle issue in this experiment was the combined effect of mental model and cognitive consistency on the user's ability to identify inconsistencies between the system's rule base and the user's problem solving procedures. The data set was subjected to a 2 x 2

analysis of variance procedure investigating the main effect of each of the independent variables as well as the interaction between them. The strong main effect of mental model, $F(1,28) = 18.67$, $p = .0002$, demonstrated that an effective understanding of the system's operating procedures facilitated rule inconsistency identification. As expected, a main effect for cognitive consistency did not occur, $F(1,28) = 2.07$, $p > .05$. The interaction between mental model and cognitive consistency, $F(1,28) = .52$, $p > .05$, was not significant.

A graphical presentation of subject correct responses as a percentage of total problems is depicted in Figure 3. The mental model/cognitive consistency interaction is easily observable. For users possessing no mental model, consistent (backward-chaining) procedures led to a significantly greater performance, than inconsistent (forward-chaining) procedure $t(14) = 2.39$, $p < .05$. For users with an accurate mental model, performance did not significantly differ for the two types of problem solving procedures $t(14) = 1.07$, $p > .05$. Users possessing an accurate mental model and consistent procedures performed significantly better than users utilizing consistent procedures with no mental model $t(14) = 2.55$, $p < .05$.

The data analysis of the 10-item subjective questionnaire revealed results supporting the performance data. Users receiving accurate mental models reported "greater confidence of their final decisions", means of 7.0 and 6.75 (cognitive inconsistent and cognitive consistent, respectively) than those without an accurate mental model, means of 4.75 and 6.5 respectively. The "adequacy of the time allotment" revealed the lowest performing group of no mental model/cognitive inconsistent to be the most time pressured, mean of

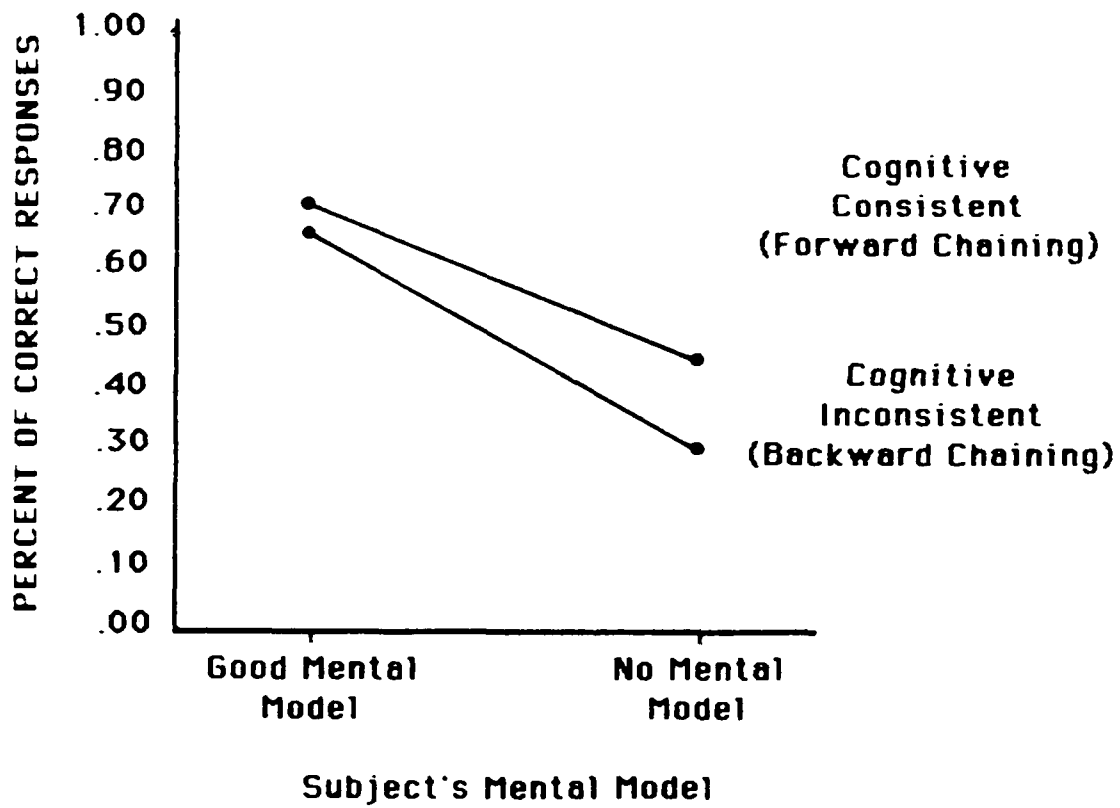


FIGURE 3
PERFORMANCE AS PERCENTAGE OF OPTIMAL RESPONSES BY GROUP
(Experiment 3)

5.25 compared to the other three groups, means of 6.0 for the no mental model/cognitive consistent group, 6.4 for the accurate mental model/cognitive consistent group, and 7.0 for the accurate mental model/cognitive inconsistent group.

The results for two items on the subjective questionnaire yielded somewhat inconsistent results. Users utilizing consistent procedures with no mental model reported "greater understanding of the system's operating procedures", mean of 7.21 followed by those users receiving a good mental model and inconsistent procedures, mean of 6.5. The no mental model group receiving inconsistent procedures had a mean of 6.1, and finally, users with a good mental model and consistent procedures had a mean of 5.1. Greater "ease of system use" was reported by the accurate mental model/cognitive inconsistent group, mean of 8.3, followed by the no mental model/cognitive consistent group with a mean of 7.75. These group means were followed by users receiving a good mental model and cognitive consistent procedures, mean of 6.8, and finally, the no mental model/cognitive inconsistent group, mean of 5.8.

The final performance measure of the number of user queries during user/system interaction revealed no significant differences across the four conditions, the means being 3.22, 3.33, 3.57, and 3.65 respectively.

DISCUSSION AND CONCLUSION

The basic conclusions for these three experiments appears to be

that in a cooperative human/intelligent machine problem solving setting, where the human and machine employ different problem solving procedures, it is generally essential that the user have an accurate model of how that machine operates. Even for relatively simple decision problems, such as the one used in these experiments, a poor mental model leads to anywhere from a 30 to 60% drop in performance. For complex, real-world expert system applications therefore a good mental model may often be a necessary condition for effective user/expert system interaction. Indeed, from the perspective of the practical implications, the most immediate impact is what the results suggests about how user interactions with expert consultation and expert interface systems will differ. Users of expert interface systems are likely to be significantly inconsistent from the expert system in both the problem specific data they are initially aware of and the domain specific heuristics utilized in problem solving. Consequently, user/expert interface system interaction is a situation that naturally reflects a great deal of cognitive inconsistency. As a result, creating an accurate mental model may be an essential ingredient for the successful transfer of interface system to operational use.

Regarding the completeness of the above research, it should be recognized that these experiments operationalized cognitive consistency as the match between the user's and the expert system's procedures. Other dimensions of cognitive consistency need to be examined. Furthermore, a node description command was the only type of explanation a user could receive in this study. This was chosen primarily because of the imposed time constraint and the nature of the

task setting. Other explanation capabilities should be examined, including a rule-trace or presentation of the system's intermediate hypotheses. Finally, user groups of diverse expertise levels should be studied over several domains and under a varying range of time constraints. Ongoing research is currently addressing further issues in the user/system interface in an attempt toward developing a more complete set of empirically-tested theoretical principles of user/expert system interaction.

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