An Application of Expectancy Theory for Assessing User Motivation to Utilize an Expert System

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ABSTRACT: Evaluation of information system success has been the focus of much research. However, most variables such as user satisfaction and system usage can only be measured after system implementation. To predict system success before actual implementation, behavioral theories indicate that it is necessary to evaluate behavioral intention or users' motivation to use the system. Expectancy theory is considered one of the most promising models of individual motivation. This study examines the use of expectancy theory in explaining the motivation to use an expert system. Data gathered from 95 M.B.A. students in a judgmental modeling exercise suggest that the model is a significant predictor of motivation. It also provides insight into the development of such systems. The successful use of this model further suggests that it is appropriate for evaluating and understanding individual motivation to use a system and, subsequently, system success.

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EXPECTANCY THEORY HAS BEEN RECOGNIZED as one of the most promising conceptualizations of individual motivation [12]. Many researchers have proposed that expectancy theory can provide an appropriate theoretical framework for research examining user acceptance of a new information system [11, 35, 51]. Such a framework could make a significant contribution to the ongoing research in IS for a measure of system success. However, empirical research on expectancy theory in the IS context has been limited. This study attempts to evaluate the appropriateness of expectancy theory in examining user acceptance of a new expert system.[1]

The paper is organized around an experimental study designed to determine if the principles of expectancy theory can explain a user's motivation to utilize a newly implemented expert system. First, prior implementation research is reviewed, followed by a discussion of expectancy theory. Next, the research methodology is discussed and the results of the experiment are critically examined. Finally, implications for research and practice are presented.

Theoretical Background and Supporting Literature

Prior Implementation Research

TWO MAJOR STREAMS OF IMPLEMENTATION RESEARCH suggested by Ginzberg [15] are implementation factor research and implementation process research. The first (factor) stream involves the identification of factors or independent variables that directly or indirectly impact some dependent variable(s) estimating implementation success. Two commonly used measures of system success have been system usage [6] and user satisfaction [8, 16, 19]. Within this stream, positive user attitude[2] (or user acceptance) is considered a critical factor that contributes to both proxies for success. The relationship between attitudes and usage has been well documented [6, 28, 35]. Similarly, user attitude toward an information system has been shown to influence user satisfaction [21, 24, 34, 35].

The second stream identified by Ginzberg [15], implementation process research, recognizes MIS implementation as a process of introducing new information system technology to the organization. As such, it is the process of introducing organizational change. User commitment to change during the implementation process is considered to have favorable impacts on system implementation. Some notable works in this stream examined related aspects of the implementation process on user attitude and system use [25, 26].

In sum, implementation research indicates that user attitude toward the changes introduced by a system are thought to be especially important to the successful implementation of MIS applications.

This would indicate that measuring user attitude toward a system is essential for assessing system implementation success. However, Turner [42] indicated that a continuing gap exists between the capabilities provided by new information systems and the extent to which these systems are accepted and used by individuals. The gap between the ability to develop and effectively use new information systems can be better explained by behavior-related elements than by elements strictly related to technical system attributes [25, 42]. These elements have not been fully captured by the attitude--success linkage described above. Also, both the factor stream and the process stream have been plagued by inconsistent empirical results. Such inconsistency in the implementation area[3] has been the subject of criticism, and is attributed to a lack of reliance on behavioral theory. Robey argued that "research in this area tends to underutilize existing knowledge in the behavioral sciences and typically fails to tie implementation research to more general models of work behavior" [35, p. 528]. Although behavior-related elements are seen as the primary cause of resistance of users toward implementation of systems, implementation research has made little use of behavioral theory.

The theory of reasoned action, as proposed by Ajzen and Fishbein [1], is a well-researched model that has successfully predicted behavior in a variety of contexts [3, 4, 13, 36, 37, 44, 45, 46, 47, 48]. They propose that attitudes and other variables (i.e., an individual's normative beliefs) do not directly influence actual behavior (e.g., usage) but are fully mediated through behavioral intentions (motivation), or the strength of one's intention to perform a specified behavior. Applying this model to explain user acceptance of information systems, Davis et al. [10] empirically determined that behavioral intentions fully mediated the effects of attitudes and all other variables on usage. They also determined, as posited by the theory, a strong relationship between behavioral intentions and actual usage. This would imply that measurement of behavioral intention to use a system is a strong and more appropriate predictor of its success.

This study describes the application of expectancy theory to measure behavioral intention or motivation to use a system. Several researchers have suggested that the adoption of an expectancy theory approach should enhance understanding of user attitude and behavior [11, 35, 51]. Accordingly, expectancy theory is used in this study as a theoretical foundation for examining the motivational and behavioral elements inherent in the process of expert system implementation.

Melone [30] proposed that, from the perspective of future information system research, expectancy models have the advantage of presenting a theoretical framework for examining information-system success via users' evaluative responses. She suggested several aspects of expectancy theory that have generally not been incorporated in past research and can be easily integrated into future work. First, the theory can integrate a "user's evaluative response with his behavioral intention" [p. 83]. A user's motivation to use a system is a function of the perceived value of that system. Second, the theory can be "easily implemented in field settings and relies on data that are available from users in most organizations" [p. 83]. Third, the basic structure of the expectancy model "permits integration of factors considered to be important in past studies examining information system success" [p. 83]. Finally, the predictive orientation of the model can change the focus of information system research from "describing to predicting and ultimately to influencing user evaluative responses" [p. 83].

Figure 1 illustrates the relationships described earlier and the use of expectancy theory to measure motivation to use a system. This is the central thrust of this study.

Expectancy Theory

Expectancy theory was originally developed by Vroom [43] and has served as a theoretical foundation for a large body of studies in psychology, organizational behavior, and managerial accounting. Expectancy models are cognitive explanations of human behavior that cast a person as an active, thinking, predicting creature in his or her environment. Individuals continuously evaluate the outcomes of their own behavior and subjectively assess the likelihood that their action will lead to those outcomes. A person's choice of the extent of effort invested is based on the systematic analysis of (1) the values of rewards from those outcomes, (2) the likelihood that rewards result from those outcomes, and (3) the likelihood of reaching those outcomes through actions [11].

According to Vroom, expectancy theory is comprised of two related models: the valence model and the force model. In our application of the theory, the valence model shows that the overall attractiveness of an expert system (V_j) is the summation of the products of the attractiveness of those outcomes associated with system use (V_k) and the likelihood that system use will be followed by those outcomes (I_{jk}):

$$V_j = \sum_{k=1}^{n} (V_k I_{jk})$$

where V_j = the valence, or attractiveness, of outcome j (first level outcome); V_k = the valence, or attractiveness, of outcome k; and I_{jk} = the perceived probability that system use will lead to outcome k.

In our case, four important potential outcomes derived from prior expert system literature[4] were incorporated in this model (i.e., $k = 4$). They are: (1) improved and more effective decision making [14, 22, 29, 38]; (2) more efficient decision making [22, 23, 29, 38]; (3) higher frequency of making correct decisions [14, 23, 29]; and (4) increased job insight through the learning stimulated by the system [22, 27, 29, 38].

The force model shows that a user's motivation to make maximum use of a new expert system (F_i) is the summation of the products of the attractiveness of the system (V_j) and the probability that a certain level of effort will result in successfully incorporating the expert system into the user's job (E_{ij}):

$$F_i = \sum_{j=1}^{n} (E_{ij} V_j)$$

where F_i = the motivational force to use an expert system at some level i; E_{ij} = the expectancy that a particular level of use (level i) will result in a certain quality of decision making; and V_j = the valence, or attractiveness, of the system.

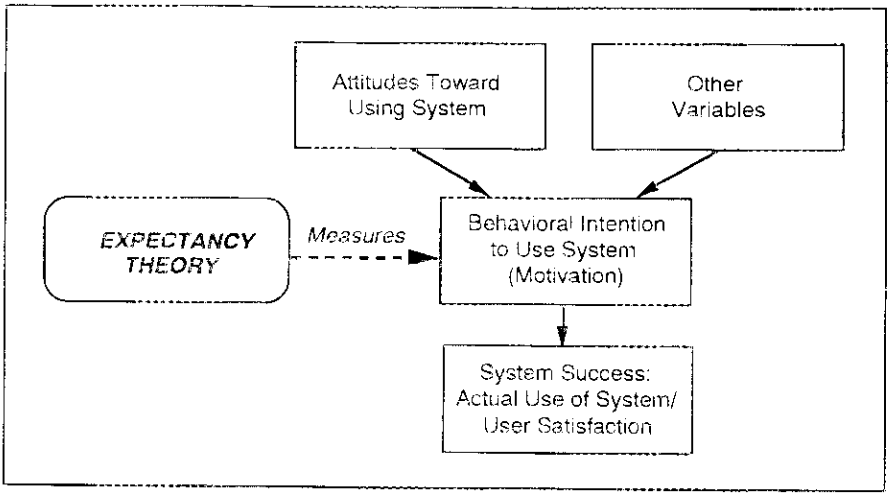

Figure 1. Relationship between Expectancy Theory and System Success

In summary, expectancy theory suggests that a user of a newly implemented expert system will continuously evaluate the outcomes of system use (e.g., increased effectiveness and efficiency of decision making, higher frequency of making correct decisions, and better understanding of the job) and subjectively assess the likelihood that his or her action will lead to those outcomes. Through an intrinsic evaluation model (valence model), with certain weights on various outcomes, an overall attractiveness of the new system is determined. The user will then use another intrinsic model (force model) to utilize the attractiveness generated before and the likelihood that his or her effort will result in successfully incorporating the expert system into the individual's job. Based on this systematic analysis, the user will determine how much effort he or she would like to exert to use the new system.

A few studies have applied expectancy theory to implementation research. DeSanctis's [11] study is a typical example. She examined the appropriateness of expectancy theory as an explanation of voluntary use of a decision support system. A controlled laboratory study was conducted in which a business simulation and its accompanying decision support system were the primary research vehicles. Eighty-eight undergraduate students participated in the study. She used an across-persons approach that compared measurements of the motivation of different individuals under a common set of circumstances. Her hypotheses relating individual expectancies to actual usage of the system were tested and yielded inconclusive results. This across-persons approach has been criticized because it violates the within-person nature and formulation of expectancy theory [49]. Furthermore, because of individual differences, the results tend to be mixed and differences among individuals are offset, often providing meaningless conclusions.

Recently, Snead and Harrell [39] applied expectancy theory to examine managers' motivation to utilize a decision support system by using a within-person analysis. Using judgmental modeling exercises relating to decision support system use, ninetyone subjects were assessed with regard to the variables relating to the expectancy theory models. Their results indicate that expectancy theory is an appropriate theoretical framework for research involving IS implementation issues. Our paper provides additional support for this framework by using a different set of variables in an expert system context.

As suggested by Snead and Harrell [39], our study uses a within-person judgment modeling decision exercise developed by Stahl and Harrell [40, 41] to examine user motivation to utilize an expert system. The within-person approach has been widely used in accounting and organizational behavior literature and is considered a more appropriate application of expectancy theory [5, 9, 17, 18].

Our intention is to follow the research direction suggested by Melone [30] by utilizing expectancy theory (1) to integrate a user's evaluative response with his or her behavioral intention, and (2) to integrate factors considered to be important in past studies examining expert system success. Our empirical results strongly support the suggestions from prior literature that expectancy theory can explain a user's motivation to use a new expert system and thereby provide further understanding of an important antecedent to system implementation success.

Research Propositions

THE RESEARCH QUESTION EXAMINED BY THIS STUDY ASKS: Can the valence and force models of expectancy theory explain the motivation of a user to make maximum use of a newly implemented expert system? Two propositions were developed:

> *Proposition 1: The valence model can explain a user's perception of the attractiveness of using a new expert system to the maximum extent.*
> *Proposition 2: The force model can explain a user's motivation to use a new expert system to the maximum extent.*

Method

Subjects

THE SUBJECTS WERE NINETY-FIVE M.B.A. STUDENTS completing an information systems course at a southeastern university. Their mean age was 25 and they had an average of 23 months full-time work experience. The students had an average of 11 months experience using computer-based information systems in their work environment. These participants were appropriate for this study because (1) they had classroom exposure to expert systems, (2) they operated a prototype expert system as a class requirement, (3) they are potential users of expert systems, and (4) they were not biased by any specific expert system environment.

While the use of student subjects has been criticized, satisfactory results using student subjects have been achieved [11, 18]. Based on a review of research in psychology, organizational behavior, marketing and accounting, Ashton and Kramer

[2] concluded that students may be adequate surrogates for business people when the research is focused on certain types of decision making.

Research Design

The within-person or individual focus of expectancy theory suggests that appropriate tests of this theory should involve comparing measurements of the same individual's motivation under different circumstances. In response to this suggestion, this study incorporates a well-established methodological approach originally developed by Stahl and Harrell [40, 41]. The methodology adapted a judgment modeling approach as proposed by Mitchell and Beach [31] and Zedeck [50] that recognizes the individual focus of expectancy theory. As described by Snead and Harrell:

> Judgment modeling involves providing an individual with a set of variables or cues which the individual must use in arriving at a particular judgment or decision. . . . Multiple sets of these cues are presented, each representing a unique combination of strengths or values associated with the cues. A separate judgment is required from the individual for each unique combination of cue strengths presented [39, pp. 11–12].

Therefore, by manipulating the combinations of levels of these variables, relative weights of each variable adapted by an individual to make the decision can be estimated.

An additional advantage of the within-person methodology is the control of extraneous variables. Since the analysis is within each subject, extraneous variables such as GMAT score, work experience, and computer experience are controlled.

Experimental Tasks

A judgment modeling decision-making exercise was developed for our expert system implementation context. This exercise was composed of sixteen cases, each representing a hypothetical, newly developed expert system in a lending environment. The participants were told that they were loan officers in a commercial bank with the responsibility of judging various loan applications and determining whether or not to approve the loans. A new expert system was available that was able to judge the financial attributes of companies subjectively and make approval decisions. Whether or not they used the system, however, the loan officers were ultimately responsible for the final decisions. Since the use of the expert system was voluntary, participants were free to decide the extent to which they would use the system.

In each of the sixteen cases the participants were asked to make two decisions. Decision *A* corresponded to the V_j in the valence model and represented the overall attractiveness of using the new system to the maximum extent, given the likelihood (10 percent or 90 percent) that the four second-level outcomes (I_{jk}) would result from their use. An advantage of providing fixed sets (10 percent, 90 percent) of I_{jk} values is reduced method bias. As mentioned earlier, the four second-level outcomes were (1) improved decision making, (2) less decision-making time, (3) more frequently correct decisions, and (4) increased job competence. Decision *B* corresponded to F_i

in the force model and reflected the strength of the participants' motivation to use the new expert system, using (1) the attractiveness of the system (V_j) obtained from Decision *A* and (2) the expectancy (E_{ij}, 10 percent or 90 percent) that, by exerting a great deal of effort, the participant would be successful in making maximum use of the expert system in his or her job.

The sixteen cases represented a one-half fractional factorial design,[5] given that sixteen (2^4) unique combinations of the four second-level outcomes and two levels of expectancy were possible.[6] The cases were presented in two different random orders to test the existence of any order effect. The instructions and a sample case of the exercise are provided in appendix 1.

A pretest was conducted with twenty-five undergraduate students. The results indicated very strong support for both models. More important is that, from the debriefing responses, the participants had little trouble comprehending the cases and they appeared to make decisions systematically by evaluating the outcomes.

Results

The First Proposition

THE FIRST HYPOTHESIS PREDICTS THAT THE VALENCE MODEL of expectancy theory can explain a user's perception of the attractiveness of making maximum use of a new expert system. The hypothesis was examined using multiple regression analysis. Decision A (V_j) served as the dependent variable, and the four second-level outcome instrumentalities (I_{jk}) served as the independent variables. The resulting standardized regression coefficients represent the relative attractiveness of each of the second-level outcomes to each participant in arriving at decision A. The mean adjusted R^2 of the ninety-five regressions with the mean standardized betas of each outcome are presented in Table 1.

As indicated in Table 1, the mean R^2 of the ninety-five within-person regression models is 0.7298, which provides explanatory evidence of the valence model in the expert systems implementation context. These results support the first proposition.

Based on the means of the standardized betas for the four second-level outcomes, referenced as V_1 through V_4, a better understanding of how participants assess the attractiveness of potential outcomes resulting from expert system implementation can be obtained. Although all four standardized betas are significant in assessing attractiveness, the participants, on average, placed relatively more valence on the first, third, and fourth outcomes ($V_1 = 0.4732$, $V_3 = 0.4413$, $V_4 = 0.4096$) and placed less valence on the second outcome ($V_2 = 0.3119$). These results imply that reaching better decisions, making correct decisions more frequently, and increasing users' understanding about their jobs contribute to the attractiveness of an expert system more significantly. Reducing users' decision-making time, however, may be less important when users assess the attractiveness of an expert system.

An additional observation from the results is the wide ranges of the betas. Such

Table 1 Valence Model Regression Results

	n	Mean	S.D.	Range
ADJ-R^2	95	0.7298	0.1436	0.3627 to 0.9653
V_1	95	0.4732	0.1545	0.1559 to 0.9713
V_2	95	0.3119	0.1519	–0.0330 to 0.8557
V_3	95	0.4413	0.1796	–0.0171 to 0.8615
V_4	95	0.4096	0.1995	–0.0358 to 0.9068

V_1: valence of better decision making; V_2: valence of less decision time; V_3: valence of more frequent correct decision making; V_4: valence of better understanding of job.

disparate ranges provide evidence that individuals do differ in their assessment of the attractiveness of second-level outcomes. This result confirms our belief that it is necessary to use a within-person analysis in the application of expectancy theory.

The Second Proposition

The second hypothesis proposes that the force model can explain a user's motivation to use a newly implemented expert system to the maximum extent. This hypothesis was also examined using multiple regression analysis. The dependent variable was the individual's level of effort to use the system (F_i) which was captured by decision B. The two independent variables were (1) each person's perception about the attractiveness of the system (V_j) from decision A, and (2) the expectancy information (E_{ij}) provided by the "Further Information" (see appendix 1). The force model results are summarized in Table 2.

The mean R^2 (0.7975) supports the second hypothesis and indicates that the force model sufficiently explains users' motivation for using a new expert system. A hierarchical regression analysis was conducted to compare the appropriateness of the full multiplicative model and the additive model. The only difference of the additive model and the multiplicative model is that the latter incorporated not only the two dependent variables but also their interaction term. The results indicate that twenty-eight out of ninety-five participants apply the multiplicative combination of attractiveness and expectancy to a significant extent (0.05 level). However, the average incremental explanatory power of the interaction term over the additive model was not significant. Thus, the additive model appears to describe implementation effort decisions made by most users adequately.

The mean standardized regression coefficients (B_1 and b_2) indicate the impact of (1) the overall attractiveness of the system (V_j), and (2) the expectation that a certain level of effort leads to successful implementation on users' motivation for using the system to the maximum extent. Our results show that both attractiveness and expectancy significantly affect users' motivation. However, on average, when considering how much effort they are willing to exert to use the system, participants weight the

Table 2 Force Model Regression Results

	n	Mean	S.D.	Range
ADJ-R^2	95	0.7975	0.1435	–0.0654 to 0.9597
b_1	95	0.6408	0.1909	–0.1559 to 0.9214
b_2	95	0.5686	0.1811	0.1890 to 0.9586

b_1: weight placed on attractiveness of the expert system; b_2: weight placed on the expectancy of successfully implementing the expert system.

attractiveness of the system slightly heavier (b_1 = 0.6408) than the expectation that they can successfully apply the system to their jobs with a certain level of effort (b_2 = 0.5686).

Experimental Controls

Pearson's Product-Moment correlations between R^2 values of valence and force models and selected demographic information (GMAT, working experience, experience of using computer-based information systems) were used to test the associations between the empirical results and participants' backgrounds. If these correlations are significant, then the strength of the relationships discussed is biased by the participants' backgrounds. Appendix 2 presents these results. No significant correlation (at the 0.05 significance level) was observed between subjects' R^2 values and their GMAT scores, prior work experience, and previous use of computer-based information systems. These results support our argument that the subjects we used were appropriate for this study because their experience in using an actual computer-based system is not correlated with their evaluation of the expert system.

In order to test whether there was any order effect, we compared the average R^2 from the two random order versions. No significant difference was found between the R^2 of the two versions. This result implies that no order effect exists in our experimental design.

Discussion and Implications

SOME LIMITATIONS OF THIS STUDY SHOULD BE DISCUSSED. First, this study used an experimental task. Subjects' responses were gathered in a controlled environment rather than in a real-world setting. Second, the levels used in the cases are extreme (10 percent and 90 percent). Such extremes may not exist in actual practice. Third, random procedures for subject selection were not employed. Therefore, caution should be used in generalizing the results to other groups and settings.

A major strength of this study is the use of a within-person approach to examine the two expectancy theory models. In addition, subjects' background factors and order effect were controlled, little method bias was involved, and a relatively large sample size was used. Prior applications of expectancy theory to the systems implementation process did not report strong results. However, the results of this study's within-person methodology strongly support that expectancy theory can be generalized to the system implementation area. The valence model significantly explains a user's assessment of the attractiveness of a new expert system (average $R^2 = 0.7298$). Further, the force model provides a good explanation of a user's motivation to use a new expert system to the maximum extent (average $R^2 = 0.7975$). Accordingly, the results of this study support the proposal of prior literature that expectancy theory provides an appropriate conceptual framework for systems implementation research.

Implications for Practice

One of the major dilemmas facing IS managers today is the difficulty in evaluating IS success [8, 33]. An associated problem is that of predicting IS success prior to or during system design and implementation. While measures such as user satisfaction and system usage are often used, they are postimplementation measures that provide little insight into the design changes that can be made to improve success. Expectancy theory, as applied in this context, attempts to look at factors that can be used to predict these success variables, such as user attitudes toward the system.

The study described in this paper provides a successful illustration of expectancy theory, using the case of an expert system. In practical terms, the results show that expectancy theory can be applied early in the design phase of system development to provide a better indication of a user's intention to use an expert system. As discussed earlier, studies related to the theory of reasoned action provide strong evidence relating behavioral intention to use. Therefore, the application of expectancy theory (1) helps close the gap between the capabilities of a new expert system and the extent to which the expert system is used, and (2) responds to the claim of previous research that the gap can be better explained by behavioral elements rather than by technical attributes. In order to maximize system success (e.g., system usage and user acceptance), systems analysts and designers may incorporate the favorable attributes (second-level outcomes) identified in the study into their expert system. Further, system developers may gauge their own effort to achieve these outcomes according to each outcome's relative importance as generated from the study.

The experiment's evaluation of an individual's intention to use an expert system under varying circumstances (within-subject design) can be adapted in a real-world context. However, care should be taken to ensure the validity of such an adaptation. For instance, key second-level outcomes based on the system's features and capabilities would have to be rigorously determined. These can often be formulated through careful systems analysis, interviews with potential users and evaluation of the business impacts of the system. In addition, the likelihood that the four outcomes would result from system use and the likelihood that the subject would make maximum use of the expert system were both held at two levels, 10 percent and 90 percent. In a practical setting, more than two extreme instrumentalities would have to be used in order to refine the conclusions drawn from this study. Such adaptation might require further experimentation in controlled settings before taking it to the field. If key second-level outcomes can readily be identified for the specific expert system, application of expectancy theory across the potential user domain can provide practical insight into the relative importance of the various outcomes---which can subsequently be the basis for system changes. While work conducted in the study is preliminary, it has promising implications for practice.

Implications for Research

The study successfully applied a behavioral theory, expectancy theory, to a system implementation area and provided an appropriate theoretical framework for future research. Many researchers conducting prior implementation research failed to incorporate behavioral elements into their studies even though user attitude toward a system was recognized as important to implementation success. Furthermore, the importance of behavioral intention as a mediating variable between attitudes and use adds to the value of this study. It can be inferred from this experiment that a user's motivation to use a system (behavioral intention) can be assessed using expectancy theory and will subsequently affect the individual's acceptance, usage, and satisfaction with the system. The results of this study should stimulate more research in the behavioral aspects of the system implementation process.

Future research should revalidate the application of expectancy theory in different IS contexts. Various factors such as top management support, user involvement, training, and organizational contexts can be examined for their impacts on the valence and force models. The relationships among attitudes, intentions, and use should be further validated. The ultimate goal of this line of research is to gain more rigorous and consistent insight into understanding IS effectiveness and our ability to preview implementation behavior.

Finally, to summarize, contributions of this study include: (1) an increased understanding of behavioral intention, (2) the ability to integrate the evaluative responses of users with behavioral intentions, and (3) the predictive orientation of the expectancy model which can change the perspective of information systems implementation research from descriptive to prescriptive.

NOTES

1. Expert systems are problem-solving computer programs that require specialized knowledge and skill to achieve good performance in a complex problem domain [14]. Many users view expert systems as a useful technology for improving their decision making. Therefore, a significant increase in the number of expert systems in the business arena can be expected [7]. In view of the foreseeable prosperity of expert systems, the question of how to design and implement a successful expert system becomes more important.

2. Attitude is determined by the individual's belief about the consequences of using the system [20].

3. For example, Ives and Olson [19] noted that of the twenty-two system success studies they reviewed, only eight claimed a positive relationship between user involvement and system success; seven showed mixed results and the remaining seven showed negative or nonsignificant results. The authors stated that future implementation research should be grounded in rigorous

research methodology that draws from established reference disciplines and "where possible, the user involvement measures should be behaviorally anchored" [p. 600].

4. Four researchers independently reviewed the expert system literature. The outcomes used in this study were consistently derived by *all* the researchers.

5. According to Montgomery [32], "if the experimenter can reasonably assume that certain high-order interactions are negligible, then information on main effects and low-order interactions may be obtained by running only a fraction of the complete factorial experiment" [p. 325].

6. One-half fractional factorial design of second level outcomes: $(2^4 \times 1/2) = 8$, combined with two levels of expectancy: $8 \times 2 = 16$.

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APPENDIX 1: Expert System Case Instructions

Assume you are a loan officer of a commercial bank charged with the responsibility of deciding upon and recommending courses of lending action involving many companies applying for loans. Your decisions and recommendations are based on your assessment of the companies' financial conditions. For example, you are asked to evaluate an applicant's ability to repay the loan based on an in-depth analysis of net operating income, financial ratios, asset quality, existing debt, cash flow, forecasts, and other representations made to you by a company's management.

A newly developed computer-based expert system is available for your use which incorporates estimated relationships among several variables, including financial statement information (ratios, cash flow, etc.), forecasts, and management's representations. Conclusions about a company's financial condition along with a loan classification and recommendation will be provided. Use of this system is voluntary; your use could range from minimum to maximum use. Minimum use essentially implies that you will continue to perform your job as you have been doing prior to the systems development. Maximum use means that you will rely on this system to a great extent in performing your job. Whether you use the system or not, you are ultimately responsible for the decisions you make.

Given this background, this exercise presents 16 situations. Each situation differs with respect to the likelihood of certain impacts associated with your making MAXIMUM use of this expert system and with respect to the probability of your being able to use the system to the MAXIMUM extent. You are asked to make two decisions for each situation. You must first decide how *attractive* it would be for you to use the expert system to the MAXIMUM extent (DECISION A). You must next decide how much *effort* you would exert to use the expert system to the MAXIMUM extent (DECISION B). Use the information provided for each situation to reach your decisions. There are no "right" or "wrong" replies, so express your true beliefs openly. A sample situation is provided on the next page and then 16 formal cases follow.

*An expert system is basically a set of computer programs and coded knowledge that interact in such a way that the system can reason and solve problems by emulating the logical processes of the human mind.

Example Questionnaire

If you use the expert system to the MAXIMUM extent in your job, the likelihood that --

your decision will be significantly better than a decision you arrive at by yourself is .... HIGH (90%)

the time required to make your decision will be reduced is .... HIGH (90%)

the frequency of making correct decisions will increase is .... HIGH (90%)

the knowledge of your job and your general level of competence will increase is .... LOW (10%)

DECISION A: With the above outcomes and associated likelihood levels in mind, indicate the attractiveness to you of using the expert system to the MAXIMUM extent in your job.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

FURTHER INFORMATION: If you exert a great deal of effort to use the expert system to the MAXIMUM extent in your job, the likelihood you will be successful in doing so is .... HIGH (90%)

DECISION B: Keeping in mind your attractiveness decision (DECISION A) and the FURTHER INFORMATION, indicate the level of effort you would exert to use the expert system to the MAXIMUM extent in your job.

0	1	2	3	4	5	6	7	8	9	10
Zero Effort										Great Deal of Effort

Appendix 2: Pearson's Product-Moment Correlation Coefficients

	GMAT	Computer experience	Work experience	R^2 force	R^2 valence
GMAT	1.0000 (0.0000)				
Computer experience	0.1857 (0.1058)	1.0000 (0.0000)			
Work experience	0.1419 (0.2183)	0.5810 (0.0001)	1.0000 (0.0000)		
R^2 force	0.1831 (0.1109)	0.1765 (0.0888)	—0.0475 (0.6491)	1.0000 (0.0000)	
R^2 valence	0.0449 (0.6976)	0.0595 (0.5683)	−0.0869 (0.4047)	0.0876 (0.3986)	1.0000 (0.0000)