An Artificial Neural Network Model Approach to Predict Managers' and Business Students' Motivational Levels Using Expert Systems

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ABSTRACTS

Historically, the end-users' acceptance of the expert systems(ES) have generally been used as a proxy for the ES' implementation success by both practitioners and academicians. However, with regard to bank loan decisions, most loan officers approach the acquisition of an ES with apprehension.

In order to overcome this skepticism, more research should focus on the behavioral aspects related to systems acquisition and usage. This research applied Vroom's (1964) expectancy theory in an effort to predict end-users' motivation to use an ES in a bank loan decision context.

Because human behaviors and judgements are nonlinear rather than linear functions, accurately predicting human behavior is very difficult. To increase the prediction power for end-users' motivation to use an ES in a bank loan decision context, this research used an artificial neural network (ANN) model.

In this research, an attempt was made to evaluate adequacy of the surrogates by analyzing differences between real bank loan officers and student surrogates in applying expectancy theory to estimate bank loan officers' motivation to use ES in a bank loan decision context.

I. INTRODUCTION

In the current business world, information and its related technologies are regarded

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as being able to provide competitive advantage for both practitioners and academicians. Successful implementation of Expert Systems (ESs) can provide competitive advantage to business companies on the grounds that ESs can make very scarce top-level expertise available to the nonexpert decision makers, which, in turn, may significantly increase those nonexpert decision makers' overall performance (Turban, 1993).

Along with many other application areas, ES have been successfully applied to bank loan decisions (Thompson and Martin, 1990). ES may provide the following benefits to the bank.

1. Increase loan managers' decision quality (Plath and Kloppenborg, 1989; Goodall, 1985; Turban, 1993; Zawa, 1991).
2. Increase novice loan managers' ability to convince others to accept and act on their decisions (Plath and Kloppenborg, 1989; Harmon and King, 1985; Turban, 1993; Zawa, 1991).
3. Increase the loan managers' chances to establish and maintain good relationships with customers (Plath and Kloppenborg, 1989; Goodall, 1985; Turban, 1993; Waterman, 1985; Zawa, 1991).

Although ES have many potential advantages, ES development is very expensive and time consuming. For example, an ES shell, IBM's AD/Cycle TIRS, costs $110,000 per package (Stylianou et al., 1992). In addition to the costs, the median time for completion of an ES is eleven person-months and the median number of rules for an ES is 190 (Philip and Schultz, 1990). Those median data values indicate that development of an ES is nontrivial and requires significant effort. Therefore, successful implementation of an ES dictates considerable emphasis if using organizations are to be provided relevant decision making information in a cost-effective manner.

Historically, the end-users' acceptance of the ES have generally been used as a proxy for the ES' implementation success by both practitioners and academicians (Lucas, 1978; Barki and Huff, 1985; Fuerst and Cheney, 1982). However, with regard to bank loan decisions, most loan officers approach the acquisition of an ES with apprehension (Plath and Kloppenborg, 1989).

In order to overcome this skepticism, more research should focus on the behavioral aspects related to systems acquisition and usage (Lovata, 1987). Among several behavioral theories which can provide a reliable prediction of user response to ES, this research applied Vroom's (1964) expectancy theory in an effort to predict end-users' motivation to use an ES in a bank loan decision context. Consequently, the research employed motivation, rather than actual usage as a surrogate for success.

Because human behaviors and judgements are nonlinear rather than linear functions, accurately predicting human behavior is very difficult (Tam and Kiang, 1992). To increase the prediction power for end-users' motivation to use an ES in a bank loan decision context, this research used an artificial neural network (ANN) model. As the basic concept of an ANN is to mimic the manner in which the human brain works (Turban, 1993), an ANN model should provide very high prediction power of end-users' motivation to use an ES in this situation.

Because many managers are reluctant to provide the needed cooperation in experimental settings (Hughes and Gibson, 1991; Abdel-Kkalik, 1974), research conducted in behavioral accounting and Management Information System (MIS) have heavily relied on students acting as surrogates for industry managers. Although the adequacy of using students as surrogates has been questioned by several researchers, no universally recognized procedures or guidelines are available yet (Hughes and Gibson, 1991). In this research, an attempt was made to evaluate adequacy of the surrogates by analyzing differences between real bank loan officers and student surrogates in applying expectancy theory to estimate bank loan officers' motivation to make maximum use of ES to the loan decision making process. Maximum use means that bank loan officers rely on ES to a great extent to the loan decision making process.

II. THEORETICAL BACKGROUND

In this study, Vroom's (1964) expectancy theory is selected to compare bank loan managers' motivation to use an ES with business students' motivation to use the ES.

1. Expectancy Theory

Vroom's expectancy theory has received a great deal of attention from academicians and practitioners. Expectancy theory is based on the assumption that the strength of motivation to act a certain way is determined by the strength of the expectation that the act will be followed by given outcomes and by the attractiveness of those outcomes to the individual (Robbins, 1991).

1.1. The Valence Model

The valence model predicts the attractiveness of a first level outcome for an individual by using second level outcomes and their respective instrumentalities. The relation equation is:

$$V_j = \sum_{k=1}^{n} V_k \, I_{jk} \qquad (j = 1,\dots,m) \tag{1}$$

In the context of this study, V_j describes the attractiveness (valence) for a research subject to make maximum usage of a newly developed ES (first level outcome). V_k describes the attractiveness (valence) of second level outcomes associated with ES use. Second level outcomes identified in prior research to be associated with ES use, and selected for this research are (1) to convince others to accept and act on an ES user's decision (Plath and Kloppenborg, 1989; Turban, 1993; Zawa, 1991; Harmon and King, 1985), (2) to establish and maintain friendly relationship with customers (Zawa, 1991; Goodall, 1985; Waterman, 1985; Plath and Kloppenborg, 1989), and (3) to increase decision quality (Turban, 1993; Goodall, 1985; Zawa, 1991; Plath and Kloppenborg, 1989). The I_{jk} value describes the likelihood that, if an ES is maximally used by a bank loan officer, the associated second-level outcomes will be forthcoming. Based on the equation, the attractiveness of a first level outcome is a function of the sum of the products of all corresponding second level outcomes and the strength of the relationship between the first level outcome and its associated second level outcomes.

1.2. The Force Model

The force model predicts the level of motivation force acting on a person to exert effort or perform an act by using the valence of the first level outcomes and the expectancies that the act will be followed by the attainment of these outcomes. The original Vroom's (1964) relationship equation is:

$$F_i = \sum_{j=1}^{n} V_j E_{ij} \qquad (i = 1, ..., m) \tag{2}$$

In this context, F_i describes a research subject's motivation (effort) to make maximum use of a new ES. V_j describes the valence associated with maximum ES use, and E_{ij} describes the expectancy (probability) that a particular level of effort will result in successfully incorporating the ES into the job. Based on the equation, the level of motivation force acting on a person to exert effort or perform an act is a function of the product of the valence of the first level outcome and the expectancy that the act will be followed by that outcome.

2. Artificial Neural Networks (ANNs)

A major barrier to applying behavioral theory in implementation research is lack of accurate measurement tools. Because of the nonlinear human judgement function, humans adapt their behaviors according to the changes of environments and accurate measurement of human behaviors is wrought with difficulty. Previous expectancy theory research has applied multiple regression or multiple discriminant techniques for analysis, but before applying these multivariate techniques, assumptions such as normality, homoscedasticity, and linearity must be examined. Therefore, results from these techniques can only be justified when the data used for the research satisfies those assumptions. Application of an ANN model to improve prediction power of an end-user's motivation to employ an ES addresses many of the previously cited problems.

ANNs are drastically different from previous multivariate techniques in that they allow for more flexibility and can be used when nonparametric techniques are required (Zurada, 1992). As a result, ANNs can be used in computationally intensive areas that are not successfully attacked by conventional statistical research. Therefore, ANNs should provide a much higher prediction power for motivation to use an ES. Currently, more than one hundred different neural network models and algorithms have been developed. Important ANNs algorithms and their properties are summarized in Table 1. Among them, back-error propagation learning, or more commonly, backpropagation is the most successful and one of the most studied learning algorithms in the neural network arena (Hecht-Nielsen, 1990) and was applied here. The flowchart of the back-error propagation algorithm is provided in Figure 1.

2.1. BACK-ERROR PROPAGATION

A back-propagating neural network is the most popular (Dayhoff, 1990) artificial neural network, which trained by supervised learning (i.e., the network is presented with an input pattern with a target output, and training process is focused to decrease the difference between the network's output and target output by adjusting weights of interconnections) via a forward-propagation step followed by a backward-propagation step.

2.1.1. Forward-Propagation

Figure 2 illustrates the specifics of the forward-propagation step. Output units are denoted by O_k, hidden units by H_j, and input units by I_i. There are connections W_{ji} from the inputs to the hidden units, and W_{kj} from the hidden units to the output units. The index i refers to an input unit, j to a hidden one, and k to an output unit. P presents the number of input patterns (μ = 1,2,..,p).

Table 1
Summary of ANNs Alorithms and Their Properties

Learning rule	Single weight adjustment Δw_{ij}	Initial weights	Learning	Neuron characteristics	Neuron /Layer
Hebban	$co_i x_j$ $j=1,2,\ldots,n$	0	U	Any	Neuron
Perceptron	$c[d_i-\mathrm{sgn}(w^t_i x)]x_j$ $j=1,2,\ldots,n$	Any	S	Binary bipolar, or binary unipolar*	Neuron
Delta	$c(d_i-o_i)f'(net_i)x_j$ $j=1,2,\ldots,n$	Any	S	Continuous	Neuron
Widrow-Hoff	$c(d_i-w^t_i x)x_j$ $j=1,2,\ldots,n$	Any	S	Any	Neuron
Correlation	$cd_i x_j$ $j=1,2,\ldots,n$	0	S	Any	Neuron
Winner-take-all	$\Delta w_{mj}=\alpha(x_j-w_{mj})$ m-winning neuron number $j=1,2,\ldots,n$	Random Normalized	U	Continuous	Layer of p neurons
Outstar	$\beta(d_i-w_{ij})$ $j=1,2,\ldots,n$	0	S	Continuous	Layer of p neurons

c, α, β are pasitive learning constants
S-supervised learning, U-unsupervised learning
*- Δw_{mj} not shown
Source: Zurada, J. M.(1992). Introduction to artificial neural systems. Saint Paul, MN: West Publishing (p. 73)

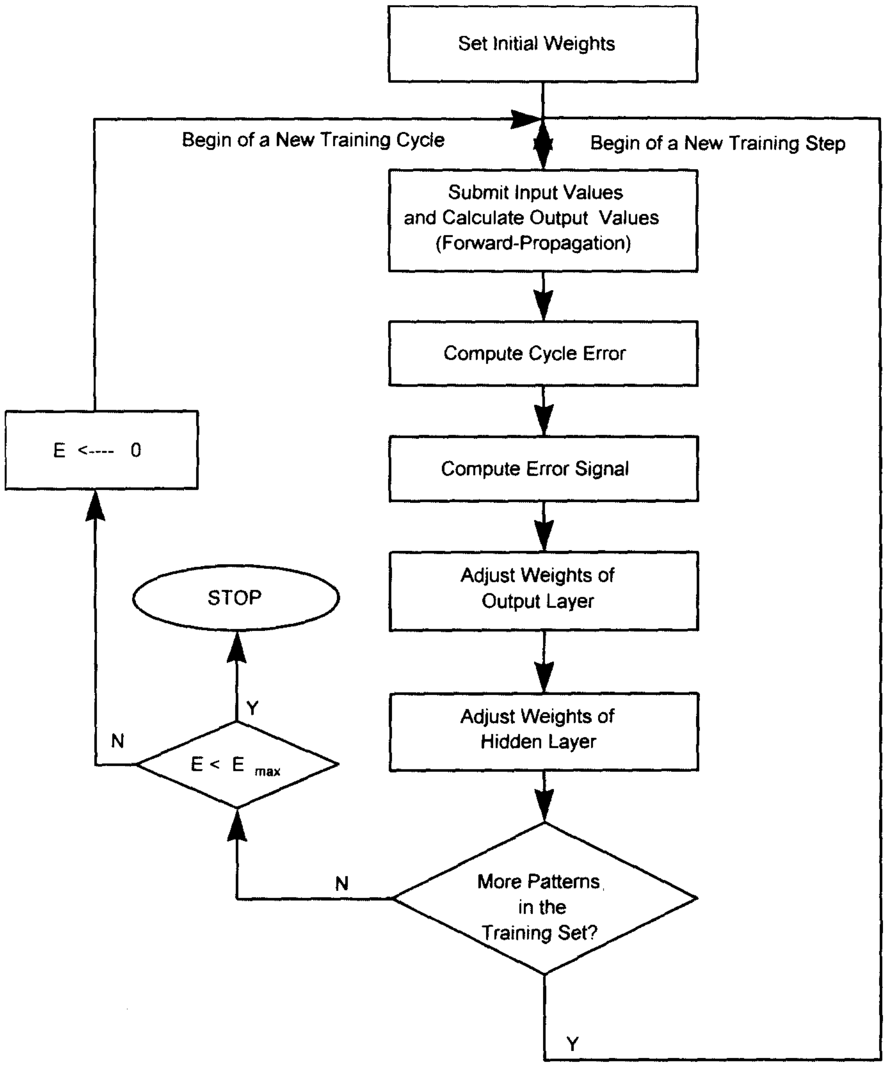


Figure 1
Back-Error Propagation Algorithm Flowchart

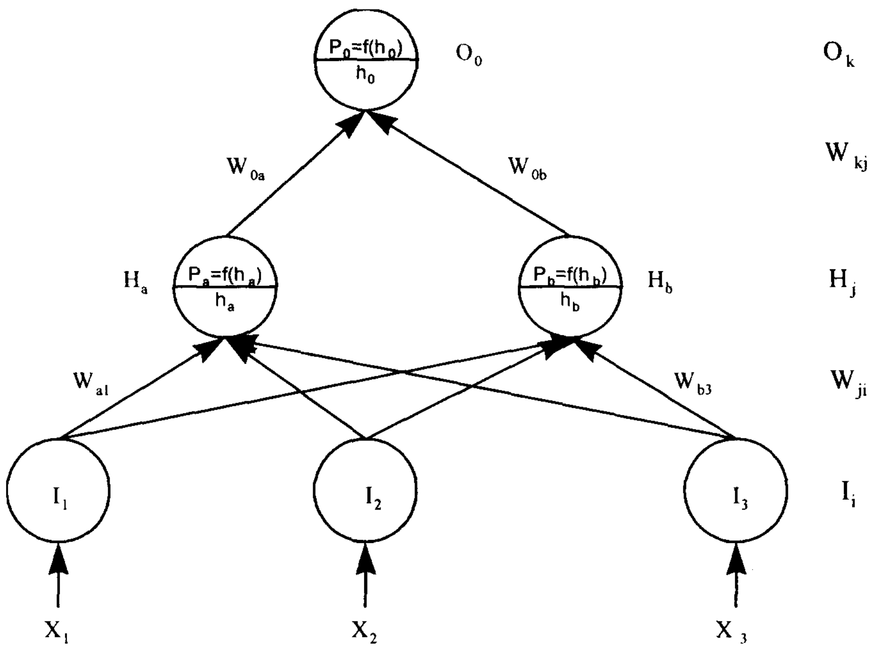


Figure 2
A Two-Layerde Forward-Propagation

Given pattern μ, hidden unit j receives a net input, which is the sum of all connections between the input layer nodes and the particular hidden node. The relationship is expressed as:

$$h_j = \sum_i W_{ji} I_i \tag{3}$$

and conducting normalization process by using a sigmoid function, and produce H_j.

$$H_j = f(h_j) = f\left(\sum_i W_{ji} I_i \right) \tag{4}$$

When bias of the unit i is considered

$$H_j = f(h_j + \theta_i) = f\left(\sum_i W_{ji} I_i + \theta_i \right) \tag{5}$$

At the same way, output unit k receives

$$h_k = \sum_j W_{kj}H_j = \sum_j W_{kj} \quad f(\sum_i W_{ji}I_i + \theta_i) \tag{6}$$

and produces for the final output

$$O_k = f(h_k) = f(\sum_j W_{kj}H_j) = f(\sum_j W_{kj} \; f(\sum_i W_{ji}I_i + \theta_i)) \tag{7}$$

Considering bias of unit j

$$O_k = f(h_k + \theta_j) = f(\sum_j W_{kj}H_j + \theta_j)$$

$$= f(\sum_j W_{kj} \; f(\sum_i W_{ji}I_i + \theta_i) + \theta_j) \tag{8}$$

In this case, f is the sigmoid function.

2.1.2. Backward-Propagation

Figure 3 illustrates the specifics of the backward-propagation step. The backward propagation is the error-correction step, and it takes place after the forward-propagation step is complete. In the first step, the target value, T_k, is compared with the output value, O_k, and the error value, δ_k, can be calculated for the output layer.

$$\delta_k = (T_k - O_k) \; f'(h_k + \theta_j) \tag{9}$$

For the hidden to output connections, the gradient descent rule gives

$$\Delta W_{kj} = - \eta \frac{\partial E}{\partial W_{kj}} = \eta \sum_{\mu} (T_k - O_k) \; f'(h_k + \theta_j)H_j$$

$$= \eta \sum_{\mu} \delta_k \; H_j \tag{10}$$

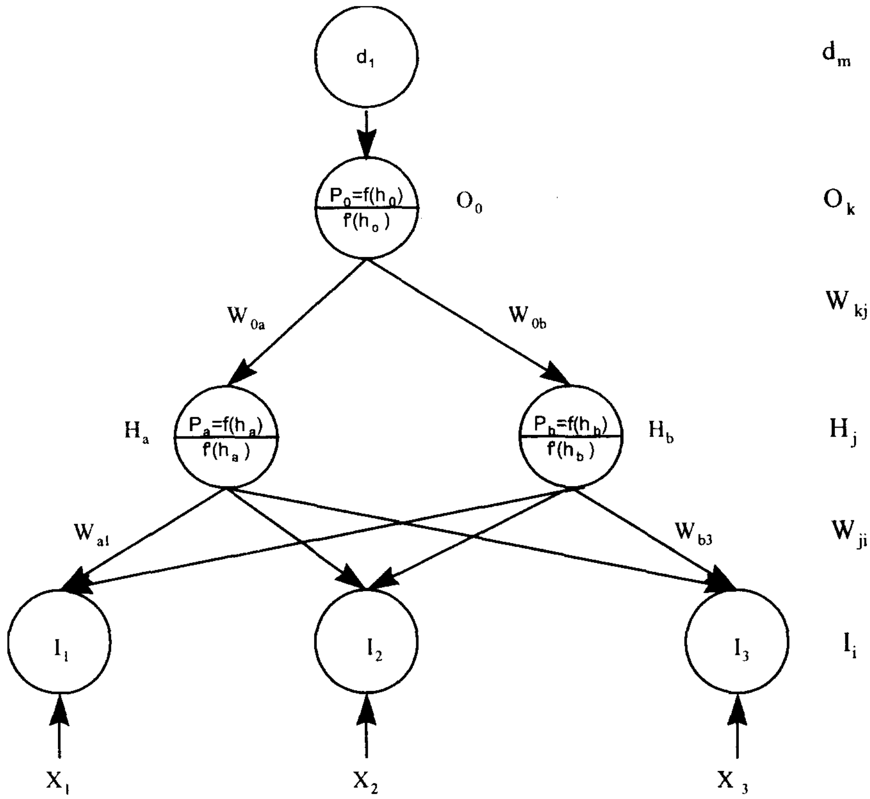


Figure 3
A Two-Layered Backward-Propagation

For the input-to-hidden connections ΔW_{ji}, differentiation with respect to the ΔW_{ji} is needed. Using the chain rule, following can be obtained.

$$\Delta Wji = -\eta \frac{\partial E}{\partial W_{ji}} = -\eta \sum_{\mu} \frac{\partial E}{\partial H_j} \frac{\partial H_j}{\partial W_{ji}}$$

$$= \eta_{\mu i} \sum (T_k - O_k)\ f'(h_k + \theta_j)\ H_j\ W_{kj}\ f'(h_j + \theta_i)\ I_i$$

$$= \eta_{\mu i} \sum \delta_k\ f'(h_j + \theta_i)\ I_i$$

$$= \eta_{\mu} \sum \delta_j\ I_i \qquad (11)$$

Note that (10) and (11) have the same form. In general, the backward propagation update rule between two layers p and q is

$$\varDelta W_{pxq} = \eta \sum_{\text{patterns}} \delta_{\text{output}} \times V_{\text{input}} \qquad (12)$$

where V stands for the appropriate input-end activation from a hidden unit or a real input, and η is the learning rate. This weight adjustment equation is known as the generalized δ rule (Rumelhart, McClelland, et al., 1986).

3. The Issue of Students as Surrogates

Most experimental research in business has used business students as subjects (Gordon et al., 1986). Approximately 75 percent of published laboratory studies in industrial/organizational psychology have employed college students (Gordon et al., 1986; Dipboye and Flanagan, 1979). The use of business students as surrogates for managers provides some apparent validity because business students will be the managers of tomorrow, and, therefore, the experimental results should be applicable to real businesses (Remus, 1986). The main reason for using student surrogates is that many managers are reluctant to provide the needed cooperation in experimental settings (Abdel-Khalik, 1974). Because there are so many experimental studies which use business students as surrogates for managers, Hall and Hall (1976) justify their use of business students in performance appraisal research as follows: "the use of undergraduate student subjects in this study is consistent with earlier research."

However, the acceptability of using students as surrogates has been questioned by researchers in many disciplines. Based on thirty-two studies, in which students and nonstudents participated as subjects, Gordon et al. (1986) found at least one significant between- subjects difference in 73 percent of the 32 investigations examined. Based on this evidence, Gordon et al. attacked the generalizability of student-surrogate experiment and suggested that studies using student subjects suffer from a lack of external validity. However, through a serious of dispute among Greenberg (1987), Gordon et al. (1987), and Dobbins et al (1988), the acceptability of student surrogates issue is still not solved yet. Although assessing the adequacy of using students as surrogates for managers is important, no universally recognized procedures or guide lines are available yet (Hughes and Gibson, 1991).

3.1. Students as Surrogates for Managers in Expectancy Theory Research

Most of the recent expectancy theory study has been conducted as experimental research; therefore a large number of studies have used student samples (e.g., Arnold, 1981; Fusilier et al., 1984; Greenhaus, Sugalski, and Crispin, 1978; Kennedy et al., 1983; Lawler et al., 1975; Matsui and Ikeda, 1976; Mitchell and Knudsen, 1973; Mitchell and Nebeker, 1973; Muchinsky, 1977a; Muchinsky and Taylor, 1976; Oldham, 1976; Schmidt and Son, 1981; Stahl and Harrell, 1981; Wheeler and Mahoney, 1981; Vroom, 1964). The widespread acceptance of the use of student samples as surrogates for business managers is illustrated by in the previous publications.

According to Kren (1990), experimental research is appropriate for expectancy theory study. This appropriateness results because: (1) experimental research allows more effective control over the variables manipulated in expectancy theory study; and (2) internal validity is more important than external validity for expectancy theory (Kren, 1990).

However, 1) the external validity weakness and 2) the use of student subjects who may not be completely representative of the subject pool of interest were two major problems to the generalizability of the findings from the expectancy theory research which used student samples (Swieringa and Weick, 1982; Kren, 1990).

3.2. Students as Surrogates for Banking Managers

In the accounting area, students as surrogates for banking managers has been well accepted. Several research efforts verify that there are no differences between business students and banking managers as experimental subjects (Mai-Dalton and Sullivan, 1981; Rosen and Jerdee, 1973; Harlan et al., 1977; Zimmer, 1980).

However, Abdel-Khalik (1974) pointed out that based on the bank loan decisions between real bank loan officers and MBA students, the students' decisions were statistically dissimilar to the bankers' decisions in about one half of the tests performed. However, Ashton and Kramer (1980) questioned appropriateness of the Abdel-Khalik's statistical methodology, and insisted that, based on their research, only 11 out of 30 tests reported significant differences between the students' decisions and the bankers's decisions.

3.3. Students as Surrogates for Managers in a Decision-making Environment

Experimental research has become one of the most popular IS research forms, and students as surrogates for managers in a decision-making has also been well accepted in the MIS area (Jarvenpaa, Dickson and DeSantis, 1985). The most famous examples are the Minnesota Experiments (Dickson, Senn and Chervany, 1977). The main rationale for using business students as surrogates for managers in decision-making environments is that business students do not change their attitude toward computer-based information systems (CBIS) when they become managers (Oz, 1990).

However, many researchers argued the adequacy of using students as surrogates for managers when the focus is the decision-making process (Burnett and Dunne, 1986; Alderfer and Bierman, 1970; Park and Lessig, 1977; Hughes and Gibson, 1991).

III. RESEARCH HYPOTHESES

Six research hypotheses were investigated for this study. The first two research hypotheses examined in this study were whether the valence and the force model of expectancy theory could be used to examine the motivation of a bank loan officer to make maximum use of an ES. Therefore, H1 and H2 in alternative form are:

H1: The valence model will explain an end-user's perception of the attractiveness of using a new ES in a bank loan decision context.

H2: The force model will explain an end-user's motivation to use a new ES in a bank loan decision context.

The next two research hypotheses examined in this study were whether ANNs provide a better technique to predict human behaviors than the multiple regression technique.

Therefore, H3 and H4 in alternative form are:

H3: ANN models have better prediction power than multiple regression models to predict end-users' perception of the attractiveness of using a new ES in a bank loan decision context.

H4: ANN models have better prediction power than multiple regression models to predict end-users' motivation to use a new ES in a bank loan decision context.

The last two research hypotheses examined in this study were whether business students are suitable surrogates for bank loan officers to examine motivation to use ES in a bank loan decision making context. Therefore, H5 and H6 in alternative form are:

H5: With regard to a bank loan decision context, bank loan officers exhibit different levels of valence than do business students.

H6: With regard to bank loan decision context, bank loan officers exhibit different levels of motivation than do business students.

IV. RESEARCH METHOD

To accomplish the research objectives, the research methodology encompasses two components. These are the selection of survey subjects and development and discrimination of the research instrument.

1. Survey Subjects

Two groups of subjects were used in this study: bank loan officers and business students. For the group of bank loan officers, a mail questionnaire was employed. Out of the 1,000 bank loan officers selected from the Polk's Bank Directory (1994), a total of 164 responses were collected. Fourteen responses were excluded because of incomplete questionnaires, thus 150 complete and usable responses were included in the data analysis. Therefore, the usable response rate was 15.0 percent. Although, because of the bank loan officers' unfamiliarity to the ES' concept and/or because of the complexity of the questionnaire, the useful response rate was only 15.0%, but it achieved reported national averages of 15% (Jung, 1991). Therefore, the response rate was minimum acceptable level. The second group of participants was 31 upper-level business undergraduate students (30 seniors and 1 junior) and 33 graduate business students. All of the students were selected at a single southeastern university. The undergraduate student completed the survey during regular class time in July, 1993. They were all enrolled in an upper division MIS class. The graduate students completed the survey during regular class time in July, 1994. The students were enrolled in a graduate level accounting or MIS class.

1.1. Nonresponse Bias Test

In this research, the bank loan officers' survey data were collected by a mail questionnaire with usable return rate of 15%. But, the business students' survey data were distributed and collected during regular class time with more than 90% usable return rate. Therefore, a nonresponse bias test was needed only for the bank loan officers.

To examine nonresponse bias, the bank's total assets were used. To verify that the distribution of the responding banks' total assets were good representatives of the distribution of the total assets of banks in the U.S., a Chi-square goodness-of-fit test was conducted. The distribution of the total assets of banks in the U.S. was available through the Thompson Bank Directory: United States (1994). Because the test statistic value of 6.138 was not more than the critical value of 6.251 (α=0.1, d.f.=3), the sampling distribution was not significantly different from the population distribution at the 0.1 level of significance (i.e., p-value > 0.1). Therefore, based on the Chi-square test for responding and nonresponding banks' total assets, there was no serious nonresponse bias.

1.2. Demographic Profile of Sample

The demographics of bank loan officers are following. Among 150 respondents, 137 (91.3%) were male and 13 (8.7%) were female. The highest frequency in age group was age 40 to under 50 (40.7%). Sixty percent of the sample respondents had a bachelor's degree. Eighty- two percent of the respondents had more than 8 years of experience in making loan decisions. Roughly one half (49.3%) of the respondents had been working more than 8 years for their current organizations.

One hundred and three (68.7%) of the respondents reported their banks have total assets of less than $100 millions. Thirty six (24%) of the responding banks reported total asset size of more than $100 millions but less than $1 billion.

The demographics of the business student participants are following. This group consisted of 33 business graduate students and 31 upper-level business undergraduate students. Among 42 male and 22 female students, one was classified as a junior (1.6%), 30 (46.9%) were classified as seniors, 13 (20.3%) were classified as masters students, and 20 (31.3%) were classified as doctoral students. Forty seven (73.4%) of participating students had a grade point average of 3.0 or higher. Thirty three of the (51.5%) participating students had taken at least 3 computer/information systems related courses and 45.5% of the students used computers to study or work more than 5 hour per week.

2. Research Instrument

After conducting a pilot study and discussing the instrument context with field-level bank officers from two banks, the initial questionnaire was refined then used to collect data. The judgement analysis approach for expectancy theory research developed by Stahl and Harrell (1981, 1983) was used to examine the motivation prediction power of the valence and force models. A factorial design was incorporated for the research. The three second-level outcomes (I_{jk}) and the expectancy variable (E_{ij}) are presented at two levels of likelihood (10 percent and 90 percent). Therefore, 16 (2^4) unique combinations of the three second-level outcome instrumentalities and expectancy were possible. Exhibit 1 is a sample case.

The questionnaire was composed of three parts. PART I was designed to examine the valence model. The three elements (convince others to accept and act on an ES user's decision; establish and maintain friendly relationship with customers; and increase decision quality) described earlier as the second-level outcomes (V_k in Equation 1) were included in

PART I. The relevance of these three outcomes to ES implementation has been addressed by prior research (Goodall, 1985; Waterman, 1985; Turban, 1990; Harmon and King, 1985; Zawa, 1991). Each element has two levels of instrumentality (10 percent and 90 percent), which correspond to I_{jk} in Equation 1. During the completion of DECISION A of the questionnaire, each subject indicated the attractiveness of using a new ES to the maximum extent, which corresponds to valence V_j in Equation 1. To enable each subject to indicate the degree of attractiveness, a 7-point Likert scale was employed with 1= very unattractive and 7= very attractive.

DECISION B of the questionnaire was designed to examine the force model. Here each subject considered the level of attractiveness (DECISION A) and two levels of expectancies (10 percent and 90 percent from PART II) together. The expectancies indicate the possibility that, if a business students exerts a great deal of effort, he/she will be successful in making maximum use of the ES in the job (E_{ij} in Equation 2). Then the subject indicated the level of effort he/she intended to exert to make maximum use of the ES in his/her job. Therefore, this effort-level decision was used to measure motivational force F_i in Equation 2. PART III of the questionnaire was designed to gather demographic information.

The business students group questionnaire was also composed of three parts. The student and loan officers questionnaires differ only with regard to the third part (demographic factors).

V. RESULTS AND DISCUSSION

1. Reliability Test

Essentially, reliability concerns the extent to which the respondent can answer the same or approximately the same questions the same way each time (Straub, 1989; Cronbach, 1951). For reliability test, Cronbach's (1951) alpha was examined for both individual items and overall measures. The overall Cronbach's coefficient alpha was

EXHIBIT 1

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

..you will increase your ability to convince others to accept and act on your decision is.......... LOW(10%)
..you will improve friendly relationship with your customer is.......... HIGH(90%)
..you will increase your decision quality is.......... LOW(10%)

DECISION A. With the factors and likelihoods shown above in mind, indicate the attractiveness to you of using the expert system to the MAXIMUM extent in your job.

1	2	3	4	5	6	7
Very Unattractive	Unattractive	Somewhat Unattractive	Neither Unattractive Nor Attractive	Somewhat Attractive	Attractive	Very Attractive

PART II. 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 using the ES in your job to the MAXIMUM extent is .... HIGH(90%)

DECISION B. With the attractiveness in DECISION A and likelihood information from PART II, indicate the level of effort you will exert to use the ES to the MAXIMUM extent in your job.

1	2	3	4	5	6	7
Zero Effort						Great Effort

* MAXIMUM extent use means that the end-user will rely on the ES to a great extent in performing his/her job.

PART I provides information relate to three Second Level Outcomes (V_k) and Instrumentalities (I_{jk})

DECISION A measures First Level Outcome or Valence level (V_j)

PART II provides information relate to Expectancy (E_{ij})

DECISION B measures Motivation Level (F_i)

0.838175. This value is well above the minimum acceptable value of 0.7 (Churchill and Suprenant, 1982). The alpha values of individual items were also far above 0.7. The lowest alpha value was 0.824465 and the highest alpha value was 0.844249. The results of the reliability test provide very strong evidence of the reliability of the measurements.

2. Validity Tests

Content validity of the research instrument is used to test whether the instrument measures adequately represent the universe of all relevant items under study (Emory and Cooper, 1991). Adequate literature review and a pretest can be used to ensure content validity. All of the second level outcomes associated with ES use were selected through the literature review and a pretest was conducted for developing the research instrument. Therefore, content validity was satisfied.

For the valence model's construct validity test, the ANOVA test for the factorial experiments was used. The ANOVA test results are summarized in Table 2. Because the p-values of CO*FR, CO*DQ, FR*DQ, and CO*FR*DQ were all more than 0.1, the interaction effect among the three variables related to the three second level outcomes was not significant. Further, as the p-values of the main factors CO (convince others), FR (friendly relationship with customers), and DQ (improve decision quality) were all less than 0.0001, the three treatments (factors) were significantly different each other. Therefore, construct validity for PART I, which was intended to test the valence model, was verified. For the force model's construct validity test, multiple discriminant analysis with the nonparametric option was used. The test results are summarized in Table 3. Because the correlations between VA (the first level outcome) and EX (expectancy) were very low (less than 0.0039), those two variables did not relate to each other. Because the F-values of the Wilks' Lambda, Pillai's Trace, Hotelling-Lawley Trace, and Roy's Greatest Root were very large (more than 279), the model had significant discriminant power. Therefore construct validity for the second part of the questionnaire, which was employed to test the force model, was verified.

3. Results of Analyses Employed to Examine H1

As mentioned earlier, H1 suggests the applicability of the valence model of expectancy theory for the end-users' perception of the attractiveness of using a new ES in the bank loan decision context. The across-persons versus within-persons methodological issue is the major controversy surrounding the use of expectancy theory to model and predict motivational force. Conventional research efforts

Table 2

The Result of Factorial Experiment ANOVA For Valence Model

Source	DF	ANOVA SS	Mean Square	F Value	P 〉 F
CO	1	896.682827	896.682827	783.24	0.0001 *
FR	1	2106.425818	2106.425818	1839.93	0.0001 *
DQ	1	1354.865070	1354.865070	1183.45	0.0001 *
CO*FR	1	1.402453	1.402453	1.23	0.2635 **
CO*DQ	1	3.112734	3.112734	2.72	0.0993 **
FR*DQ	1	0.098715	0.098715	0.09	0.7691 **
CO*FR*DQ	1	4.023949	4.023949	3.51	0.0610 **

* Significant discriminant power at $\alpha=0.05$

** No significant interaction at $\alpha=0.05$

Table 3

The Result of MDA With Nonoarametric Option For Force Model

Pooled Within-Class	Correlation Coefficients	/ Prob 〉 | R |
Variable	VA	EX
VA	1.00000 0.0	-0.51181 0.0001
EX	-0.51181 0.0001	1.00000 0.0

Between-Class	Correlation Coefficients	/ Prob 〉 | R |
Variable	VA	EX
VA	1.00000 0.0	0.91417 0.0039
EX	0.91417 0.0039	1.00000 0.0

Total-Sample Correlation	Correlation Coefficients	/ Prob 〉 | R |
Variable	VA	EX
VA	1.00000 0.0	0.00001 0.0001
EX	0.00000 0.0001	1.00000 0.0

Statistic	Value	F	Num DF	Den DF	P 〉 F
Wilks' Lambda	0.30253860	407.3968	12	5976	0.0
Pillai's Trace	0.71851473	279.3166	12	5978	0.0
Hotelling-Lawley Trace	2.23577440	556.5215	12	5974	0.0
Roy's Greatest Root	2.20420340	1098.0610	6	2989	0.0

examining expectancy theory used the across-persons approach (Ferris, 1977; Dillard, 1979; Jiambalvo, 1979; Wahba and House, 1974; Schwab, Olian-Gottlieb and Heneman, 1979; Batlis and Waters, 1973; Smith, Ascough and Ettinger, 1976; Henson, 1976; Polczynski and Shirland, 1977). However, the majority of recent research efforts examining expectancy theory have used within-persons approach (Rynes and Lawler, 1983; Harrell and Stahl, 1984; Butler and Womer, 1985; Harrell et al., 1985; Snead, 1991). Because of this shift in the research community, the within-persons methodology was chosen.

The multiple regression technique has been the most popular analysis technique for the within-persons approach of expectancy theory (Schmidt, 1973; Arnold and Evans, 1979; Baker and et al., 1989; Stahl and Harrell, 1981; Stahl and Grigsby, 1987; Zedeck, 1977; Ravichandran and et al., 1989; Griffin and Harrell, 1991; Harrell and Stahl, 1984; Harrell, Caldwell, and Doty, 1985; Snead, 1991). Following this methods, 214 (150 bank loan officers and 64 business students) individual regression models were estimated for the sample to test H1. The dependent variable was the valence measure obtained from DECISION A of the questionnaire, and the independent variables were the instrumentality measures of the three second level outcomes from PART I. Figure 4 shows the relationship.

The valence regression model used to test H1 is:

$$V_j = \beta_0 + \beta_1(I_{j1}) + \beta_2(I_{j2}) + \beta_3(I_{j3}) + \varepsilon \qquad (j= 1,\dots,m)$$

where: V_j = the perceived attractiveness of the first level outcome of maximum ES use (DECISION A)

I_{ji} = the instrumentalities, which linking the first level outcome of aximum ES use with the second level outcomes (10% and 90% values given)

β_i = standardized regression coefficients of second level outcome values Convince others; Friendly relationship with customers; and Increase decision quality)

ε = random error

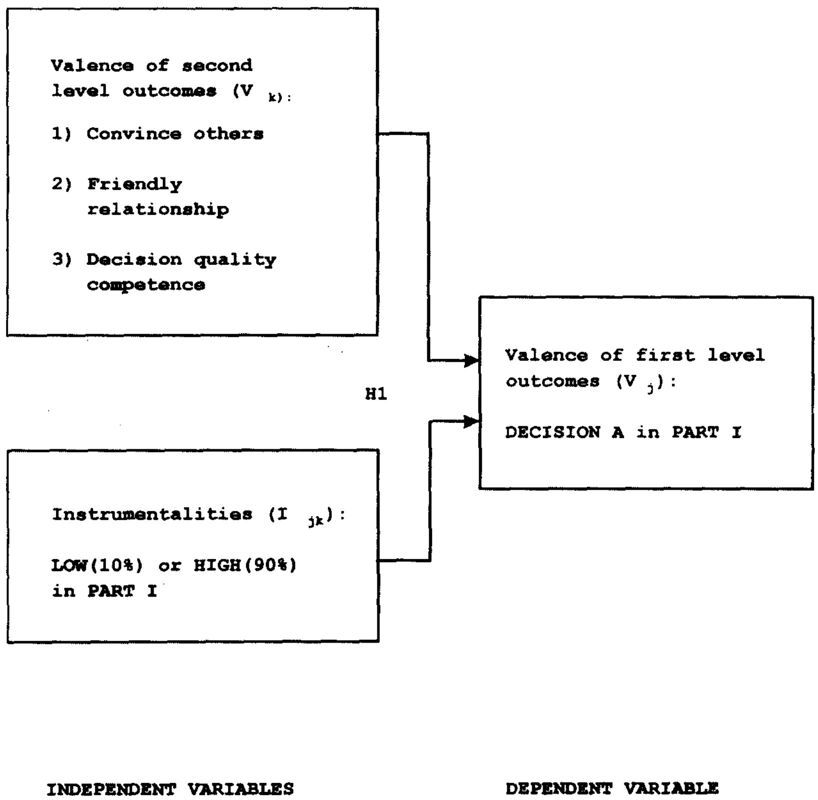


Figure 4
Diagram for the Relationship of Hypothesis

Based on the results, at the α=0.1 level (i.e., p-values were less than 0.1), all of the models achieved significance. Therefore, at the α=0.1 level, data for all of the subjects supports the applicability of the valence model in the area of bank loan managers' implementation of ES, and thus supports hypothesis H1.

Table 4 presents summary information of the regression data analysis, and provides a composite, for all 214 valence models', mean R2, mean β values, standard deviations and range values. From the table, the mean R^2 of 0.9083 is further evidence of strong support for hypothesis H1.

To determine the relative importance of the three second level outcome instrumentalities, standardized coefficients were used. Based on the mean values in Table 4, the research subjects placed the highest weight on improving friendly relationship with customers (β_2), then on outcomes related to increase decision quality (β_3) and finally to increasing the ability to convince others to accept and act on

Table 4
Summary of Valence Regression Models (All Subjects)

	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	214	0.4050	0.2077	-0.1723	0.9111
β_2	214	0.6007	0.2099	-0.0739	0.9703
β_3	214	0.4941	0.2145	-0.1796	0.9898
R^2	214	0.9083	0.0713	0.7059	0.9899

β_1 : Each subject's reaction to increase ability to convince others to accept and act on his/her decision.
β_2 : Each subject's reaction to improve friendly relationship with customers
β_3 : Each subject's reaction to increase his/her decision quility

his/her decision (β_1).

Table 5 presents summary data for the 150 bank loan officers' valence models, and Table 6 presents summary data for the 64 business students' valence models. The mean $R^2$are 0.9048 for bank loan officers, and 0.9167 for business students. The bank loan officers placed the highest weight on improving friendly relationship with customers (β_2), then on outcomes related to increase decision quality (β_3) and finally to increasing the ability to convince others to accept and act on his/her decision (β_1). In contrast, from Table 6, the business students placed the highest weight on increasing decision quality (β_3), then on outcomes related to improve friendly relationship with customers (β_2), and finally to increase the ability to convince others to accept and act on his/her decision (β_1).

Table 5
Summary of Valence Regression Models (Bank Loan Officers)

	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	150	0.3772	0.2061	-0.1723	0.9111
β_2	150	0.6462	0.2010	-0.0474	0.9703
β_3	150	0.4540	0.2175	-0.1796	0.9249
R^2	150	0.9048	0.0778	0.7059	0.9899

Table 6
Summary of Valence Regression Models (Business Students)

	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	64	0.4704	0.1980	0.0000	0.8733
β_2	64	0.4940	0.1921	-0.0739	0.8724
β_3	64	0.5883	0.1758	0.0836	0.9898
R^2	64	0.9167	0.0509	0.8033	0.9864

4. Results of Analyses Employed to Examine H2

Hypothesis H2 deals with the applicability of Vroom's (1964) force model of expectancy theory for motivation to use an ES in the bank loan decision context. Because the analysis required for testing H2 was very similar to the analysis required for examination of H1, the within-persons multiple regression analysis approach was also employed to test H2.

Again 214 individual regression models were estimated for the sample. The dependent variable was the motivation measure obtained from DECISION B of the questionnaire, and the independent variables were the perceived attractiveness of the first level outcome of maximum ES use (Decision A) and the expectancy (probability) from PART II that the effort to use the ES to the maximum extent will be successful. Figure 5 shows the relationship.

The force regression model used to test H2 is:

$$F_i = \beta_0 + \beta_1(V_j) + \beta_2(E_{ij}) + \varepsilon \qquad (i=1,\ldots,m)$$

where: F_i = the motivation (intended effort) level subject is willing to exert to use ES to the bank loan decision context (Decisions B)

V_j = the perceived attractiveness of the first level outcome of maximum ES use

E_{ij} = the expectancy (probability) that effort to use the ES to the maximum extent will be successful

β_1 = standardized regression coefficients of first level outcome value

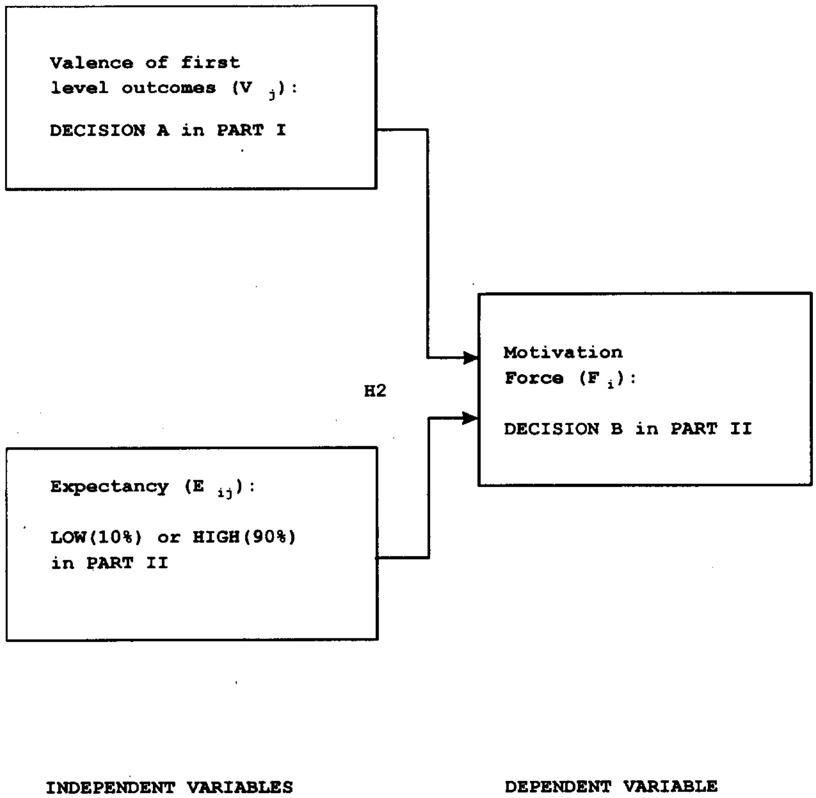


Figure 5
Diagram for the Relationship of Hypothesis

β_2 = standardized the regression coefficient of expectancy

ε = represents random error

Based on the results, at α=0.05, all 214 models achieve significance. And support the applicability of the force model in the area of bank loan managers' motivation to use ES in the bank loan decisions context. Hypothesis H2 can thus be supported.

Table 7 shows summary information of the regression analysis, and provides all of the 214 force models' mean R^2, mean β values, standard deviations and range values. From the table, the average R2 of 0.8402 provides further strong supporting evidence for hypothesis H2.

Table 7
Summary of Force Regression Models (All Subjects)

	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	214	0.6356	0.1850	0.0559	0.9689
β_2	214	0.6020	0.2004	0.0600	0.9690
R^2	214	0.8402	0.1025	0.4915	0.9870

β_1 : The perceived attractiveness of all the first level outcome of maximu

β_2 : The expectancy (probability) that effort to use the ES to the maximum extent will be successful.

To determine the relative importance of the valence and expectancy for motivation level (DECISION B), standardized coefficients were used. Based on the mean values in Table 7, subjects placed higher weight on the perception of the attractiveness of implementation (β_1) than on the expectation that their effort would be successful (β_2). This can be seen because the mean for the expectancy term (β_1) of 0.6386 was higher than the mean for the valence term (β_2) of 0.6020.

Table 8 provides summary data for the 150 bank loan officers' force models, and Table 9 provides summary data for the 64 business students' force models. The mean R^2 are 0.8143 for bank loan officers, and 0.9008 for business students. The bank loan officers placed higher weight on the expectation that their effort would be successful (β_2) than on the perception of the attractiveness of implementation (β_1). This can be seen because the mean for the expectancy term (β_2) of 0.6134 was higher than the mean for the valence term (β_1) of 0.6113.

In contrast, the business students placed a higher weight on the perception of the attractiveness of implementation (β_1) than on the expectation that their effort would be successful (β_2). This can be seen because the mean for the valence term (β_1) of 0.6926 was higher than the expectancy term (β_2) of 0.5751

Table 8

Summary of Force Regression Models (Bank Loan Officers)

	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	150	0.6113	0.1725	0.0559	0.9689
β_2	150	0.6134	0.1877	0.0956	0.9690
R^2	150	0.8143	0.1065	0.4915	0.9870

Table 9
Summary of Force Regression Models (Business Students)

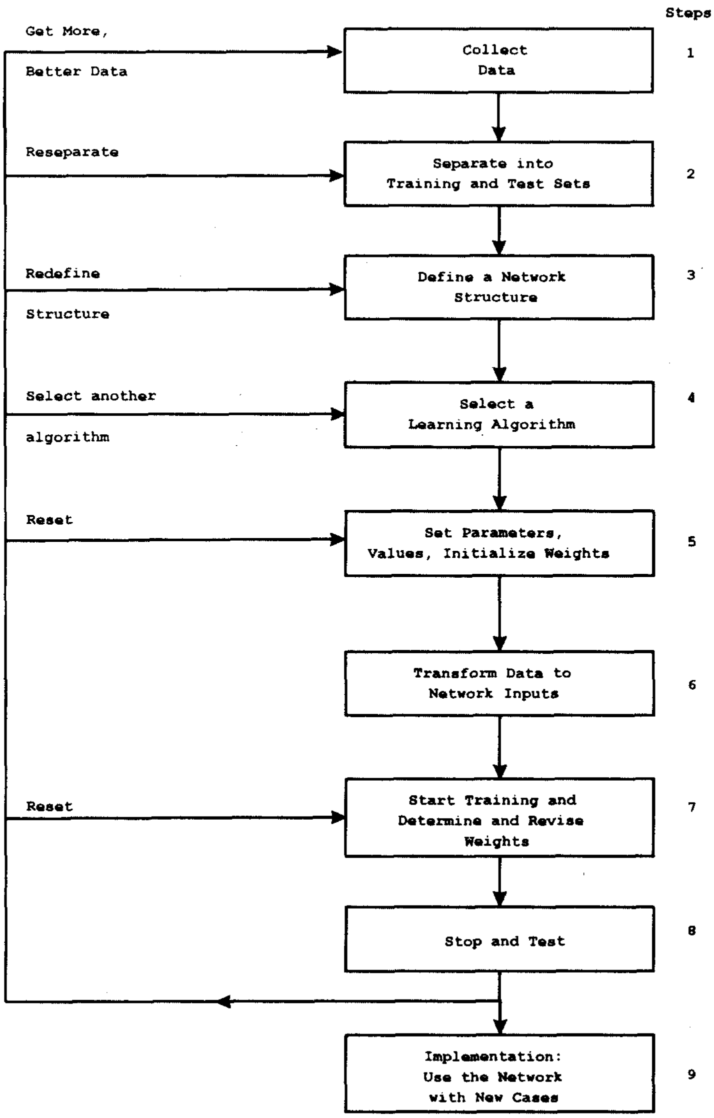
	n	Mean	Standard Deviation	Range	
				Min.	Max.
β_1	64	0.6926	0.2016	0.2051	0.9689
β_2	64	0.5751	0.2267	0.0600	0.9468
R^2	64	0.9008	0.0581	0.6828	0.9870

5. Results of Analyses Employed to Examine H3

Following Turban's (1993) nine-step development process (shown in Figure 6), ANN models were developed for the valence model, and the models' prediction power was compared with the prediction power of the multiple regression models. The ANN model is shown in Figure 7.

For the learning algorithm, a back-error propagation algorithm was selected. Therefore, the network structure was a multilayer (two layer) network of continuous perceptrons (i.e., using sigmoid function). The ANNs' learning mode was supervised learning. Furthermore, since there were no interconnections between the output of a processing element and the input of a node on the same layer or on a preceding layer, the recall mode was feed forward. However, feedback was used to adjust the weights until all training patterns were correctly categorized by the ANNs.

NETS version 2.0, developed by the AI section of NASA's Johnson Space Center, was used to develop the ANN model. NETS utilizes the generalized delta algorithm, which is the most popular sub-algorithm of back-error propagation (Rumelhart et al., 1986).



Source: Turban, E (1993). Decision Support and Expert Systems. New York, NY: Macmillan Publishing Co. (p. 639).

Figure 6
Flow Diagram of the Development Process of an ANN

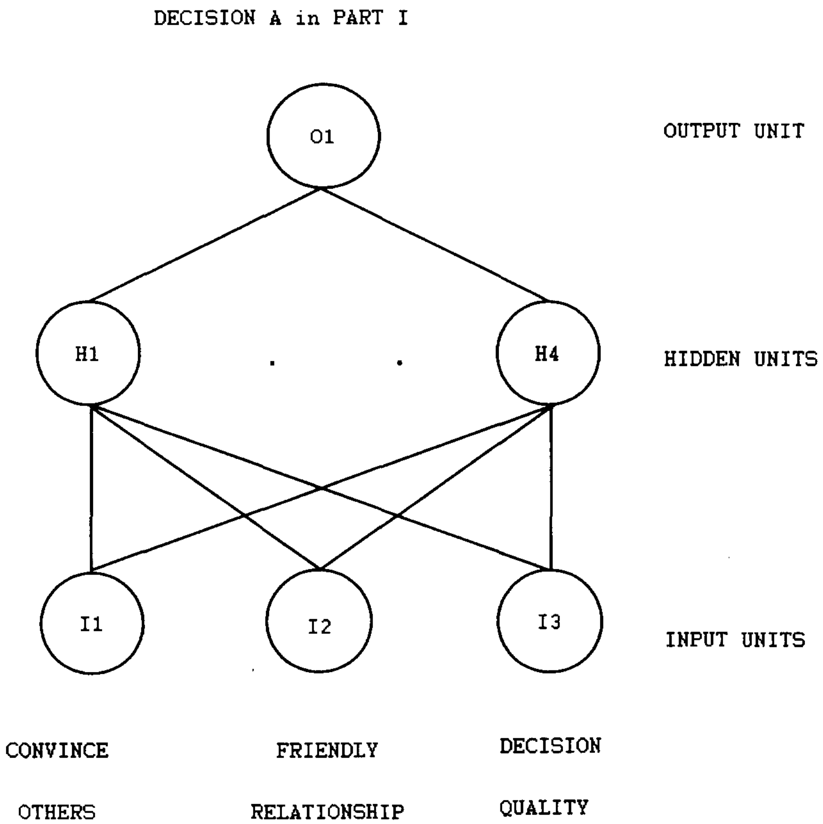


Figure 7
Flow Diagram of the Development Process of an ANN

Each subjects should answer 16 questions in DECISION A. Therefore, total responses of the 214 research subjects were 3424. Among those responses, 1712 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 1712 responses were used to test the models. Table 10 shows the prediction power of the multiple regression models and the ANNs models for all research subjects.

Note that the 'Hit Ratio' was calculated comparing the real response (observation) value and predicted value. Predicted values, which were generated by either the multiple regression models or the ANN models, were rounded up from the first digit. Therefore, for example, the predicted response of 4.8 was classified as 5. Therefore, the 'Hit ratio' indicates how many pairs of real observation responses and predicted responses exactly matched.

In total, 1015 out of 1712 (59.3%) predicted responses generated from the multiple

Table 10
Summary of Multiple Regression vs. ANNs
For the Valence Model (All Subjects)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
1015/1712 (59.3%)	5.660	1633/1712 (95.4%)	1.826

Test statistic value

F_{calc} = 5.660/1.826 = 3.100

Critical value

$F_{0.01,\ 213,\ 213}$ = 1.000

Conclusion

Significant difference at $\alpha=0.01$

regression exactly matched the real observation responses. In contrast, 1633 out of 1712 (95.4%) predicted responses generated from the ANN models exactly matched the real observation responses. Total SSE for multiple regression was 5.660, and the total SSE for the ANNs was 1.826. Therefore, the F test statistic value was 3.100 (5.660/1.826). The critical F value with α = 0.01, v_1=213, and v_2=213 degrees of freedom was 1.000. Because the test statistic value of 3.100 was well above the critical value of 1.000, the null hypothesis of equal variances could be rejected. As a result, it can be concluded that the variances from the multiple regression models were significantly larger than the variances from the ANN models. This means that ANN models have significantly better prediction power than multiple regression technique, and thus support hypothesis 3.

Table 11 shows the prediction power of the multiple regression models and the ANNs models for bank loan officers. Among the 2400 total bank loan officers' responses, 1200 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 1200 responses were used to test the models.

In total, 674 out of 1200 (56.2%) predicted responses generated from the multiple regression exactly matched the real observation responses. In contrast, 1143 out of 1200 (95.3%) predicted responses generated from the ANN models exactly matched the real observation responses. Total SSE for multiple regression was 4.335, and the total SSE for the ANNs was 1.307. Therefore, the F test statistic value was 3.317 (4.335/1.307). The critical F value with α = 0.01, v_1=149, and v_2=149 degrees of freedom was 1.000. Because the test statistic value of 3.317 was well above the critical value of 1.000, the null hypothesis of equal variances could be rejected. As a result, it can be concluded that the variances from the multiple regression models

Table 11
Summary of Multiple Regression vs. ANNs
For the Valence Model (Bank Loan Officers)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
674/1200 (56.2%)	4.335	1143/1200 (95.3%)	1.307

Test statistic value

F_{calc} = 4.335/1.307 = 3.317

Critical value

$F_{0.01,\ 149,\ 149}$ = 1.000

Conclusion

Significant difference at α=0.01

were significantly larger than the variances from the ANN models. This means that ANN models have significantly better prediction power than multiple regression technique, and thus support hypothesis 3.

Table 12 shows the prediction power of the multiple regression models and the ANNs models for business students. Among the 1024 total business students' responses, 512 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 512 responses were used to test the models.

Table 12
Summary of Multiple Regression vs. ANNs
For the Valence Model (Business Students)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
341/512 (66.6%)	1.325	490/512 (95.7%)	0.519

Test statistic value

F_{calc} = 1.325/0.519 = 2.553

Critical value

$F_{0.01,\ 63,\ 63}$ = 1.800

Conclusion

Significant difference at α=0.01

In total, 341 out of 512 (66.6%) predicted responses generated from the multiple regression exactly matched the real observation responses. In contrast, 490 out of 512

(95.7%) predicted responses generated from the ANN models exactly matched the real observation responses. Total SSE for multiple regression was 1.325, and the total SSE for the ANNs was 0.519. Therefore, the F test statistic value was 2.553 (1.325/0.519). The critical F value with α = 0.01, v_1=63, and v_2=63 degrees of freedom was 1.800. Because the test statistic value of 2.553 was well above the critical value of 1.800, the null hypothesis of equal variances could be rejected. As a result, it can be concluded that the variances from the multiple regression models were significantly larger than the variances from the ANN models. This means that ANN models have significantly better prediction power than multiple regression technique, and thus support hypothesis 3.

6. Results of Analyses Employed to Examine H4

The test process for hypothesis 4 was similar to the test process for hypothesis 3. The ANN model is shown in Figure 8. Here each of the 214 subject evaluated 16 choices with hypothetical ESs resulting in 3424 responses. Again, 1712 responses (8 for each subjects) were used to develop ANN and multiple regression models, and the other 1712 responses were used to test the models.

Table 13 provides summary information for the responses. In total, 873 out of 1712 (50.99%) of the predicted responses generated from the multiple regression exactly matched the real observation responses.

Table 13
Summary of Multiple Regression vs. ANNs
For the Force Model (All Subjects)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
873/1712 (50.99%)	9.966	1273/1712 (74.36%)	4.864

Test statistic value

F_{calc} = 9.966/4.864 = 2.049

Critical value

$F_{0.05,\ 213,\ 213}$ = 1.000

Conclusion

Significant difference at α=0.05

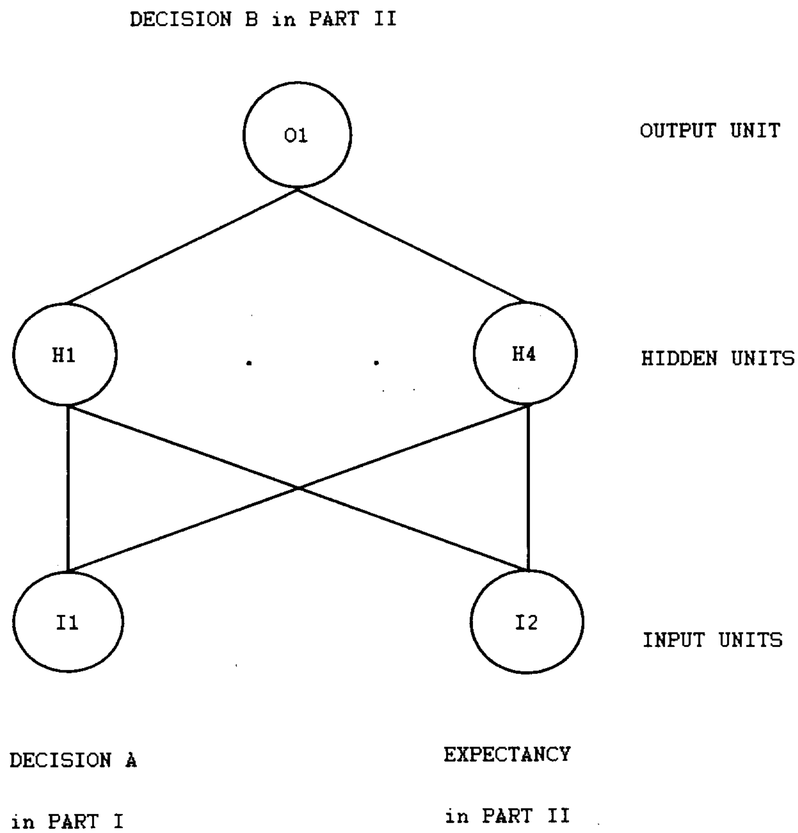


Figure 8
The ANNs for Hypothesis 2

In contrast, 1273 out of 1712 (74.36%) predicted responses generated from the ANN models exactly matched the real observation responses. The total SSE for multiple regression was 9.966, and the total SSE for ANNs was 4.864. Therefore, the F test statistic value was 2.049 (9.966/4.864). The critical F value with α = 0.05, v_1=213, and v_2=213 degrees of freedom is 1.000. And therefore, the null hypothesis of equal variances could be rejected, and it can be concluded that the variances from the multiple regression models were significantly larger than the variances from the ANN models. This means that the ANN models have significantly better prediction power than the multiple regression technique, and thus support hypothesis 4.

Table 14 shows the prediction power of the multiple regression models and the ANNs models for bank loan officers. Among the 2400 total bank loan officers' responses, 1200 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 1200 responses were used to test the models.

Table 14
Summary of Multiple Regression vs. ANNs
For the Force Model (Bank Loan Officers)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
552/1200 (46.0%)	8.047	893/1200 (74.4%)	3.729

Test statistic value

F_{calc} = 8.047/3.729 = 2.158

Critical value

$F_{0.05,\ 149,\ 149}$ = 1.000

Conclusion

Significant difference at $\alpha=0.05$

In total, 552 out of 1200 (46.0%) predicted responses generated from the multiple regression exactly matched the real observation responses. In contrast, 893 out of 1200 (74.4%) predicted responses generated from the ANN models exactly matched the real observation responses. Total SSE for multiple regression was 8.047, and the total SSE for the ANNs was 3.729. Therefore, the F test statistic value was 2.158 (8.047/3.729). The critical F value with α = 0.05, v_1=149, and v_2=149 degrees of freedom was 1.000. Because the test statistic value of 2.158 was well above the critical value of 1.000, the null hypothesis of equal variances could be rejected. As a result, it can be concluded that the variances from the multiple regression models were significantly larger than the variances from the ANN models. This means that ANN models have significantly better prediction power than multiple regression technique, and thus support hypothesis 4.

Table 15 shows the prediction power of the multiple regression models and the ANNs models for business students. Among the 1024 total business students' responses, 512 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 512 responses were used to test the models.

In total, 321 out of 512 (62.7%) of the predicted responses generated from the multiple regression exactly matched the real observation responses.

In contrast, 380 out of 512 (74.2%) predicted responses generated from the ANN models exactly matched the real observation responses. The total SSE for multiple regression was 1.919, and the total SSE for ANNs was 1.135. Therefore, the F test

Table 15
Summary of Multiple Regression vs. ANNs
For the Force Model (Business Students)

MR		ANN	
Hit Ratio	Total SSE	Hit Ratio	Total SSE
321/512 (62.7%)	1.919	380/512 (74.2%)	1.135

Test statistic value

F_{calc} = 1.919/1.135 = 1.691

Critical value

$F_{0.05,\ 63,\ 63}$ = 1.500

Conclusion

Significant difference at $\alpha=0.05$

statistic value was 1.691 (1.919/1.135). The critical F value with α = 0.05, v_1=63, and v_2=63 degrees of freedom is 1.500. And therefore, the null hypothesis of equal variances could be rejected, and it can be concluded that the variances from the multiple regression models were significantly larger than the variances from the ANN models. This means that the ANN models have significantly better prediction power than the multiple regression technique, and thus support hypothesis 4.

7. Results of Analyses Employed to Examine H5 and H6

These hypotheses were used to examine whether significant differences exist between students and bank managers for valence levels (H5) and motivation levels (H6) in regard to use ES to bank loan decisions. To test H5 and H6, several statistical methods were considered together: ANOVA, Wilcoxon Rank Sum Test, Kruskal-Wallis Test and Median Test were conducted. The test results for the H5 are summarized in Table 16. For the valence model (response scores for the PART I), the mean response score for the bank loan officers was 3.6808, and the mean response score for the business students was 3.9941. Because the p-values of ANOVA (0.0034), Wilcoxon Rank Sum Test (0.0023), Kruskal-Wallis Test (0.0023) and Median Test (0.0209) were all less than 0.05, the null hypothesis of identical response level between bank loan officers and business students was rejected. The conclusion based on the test result was that business students demonstrated significantly higher valence level to the maximum usage of an ES than the valence level of the bank loan officers, and thus H5 was supported.

Table 16

Valence Level Comparison Between Bank Loan Officers and Business

ANOVA				
Treatment	n	Mean	F value	Prob 〉 F
1	2400	3.68083333	8.586	0.0034
2	1024	3.99414062		

Wilcoxon Scores (Rank Sums)		
S = 466805	Z = 3.05277	P 〉 |Z| = 0.0023
T-Test approx. Significance = 0.0023		

Kruskal-Wallis Test (Chi-Square Approximation)		
Chi-Square = 9.3197	DF = 1	P 〉 Chi-Square = 0.0023

Median Scores					
Median 2-Sample Test (Normal Approximation)			Median 1-Way Analysis (Chi-Square Approximation)		
S = 226.000	Z= 2.30987	P 〉 |Z| = 0.0209	Chi-Square 5.3355	DF = 1	P 〉 Chi-Sq. = 0.0209

The test results for the H6 are summarized in Table 17. For the force model (response scores for the PART II), the mean response score for the bank loan officers was 2.8905, and the mean response score for the business students was 3.4297. Because the p-values of ANOVA (0.0001), Wilcoxon Rank Sum Test (0.0001), Kruskal-Wallis Test (0.0001) and Median Test (0.0001) were all less than 0.05, the null hypothesis of identical response level between bank loan officers and business students was rejected. The conclusion based on the test result was that business students demonstrated significantly higher motivation level to the maximum usage of an ES than the motivation level of the bank loan officers, and thus H6 was supported. From Table 18 considering valence level motivation level together, business student showed significantly favorable response in regarding to use ES. In summary, participated business students revealed much higher valence level and motivation level than bank loan officers.

Table 17

Force Level Comparison Between Bank Loan Officers and Business S

ANOVA				
Treatment	n	Mean	F value	Prob 〉 F
1	2400	2.89047619	46.606	0.0001
2	1024	3.42968750		

Wilcoxon Scores (Rank Sums)		
S = 1507105	Z = 7.76035	P 〉 |Z| = 0.0001
T-Test approx. Significance = 0.0001		

Kruskal-Wallis Test (Chi-Square Approximation)		
Chi-Square = 60.223	DF = 1	P 〉 Chi-Square = 0.0001

Median Scores					
Median 2-Sample Test (Normal Approximation)			Median 1-Way Analysis (Chi-Square Approximation)		
S = 551.000	Z= 8.55314	P 〉 |Z| = 0.0001	Chi-Square 73.156	DF = 1	P 〉 Chi-Sq. = 0.0001

Table 18
Overall Response Level Comparison
Between Bank Loan Officers and Business Students

ANOVA				
Treatment	n	Mean	F value	Prob 〉 F
1	4800	3.17787879	50.202	0.0001
2	2048	3.63494318		

Wilcoxon Scores (Rank Sums)		
S = 3645510	Z = 7.86378	P 〉 |Z| = 0.0001
T-Test approx. Significance = 0.0001		

Kruskal-Wallis Test (Chi-Square Approximation)		
Chi-Square = 61.839	DF = 1	P 〉 Chi-Square = 0.0001

Median Scores					
Median 2-Sample Test (Normal Approximation)			Median 1-Way Analysis (Chi-Square Approximation)		
S = 708.000	Z= 6.75934	P 〉 |Z| = 0.0001	Chi-Square 45.689	DF = 1	P 〉 Chi-Sq. = 0.0001

VI. CONCLUSIONS

The results of this research verify that expectancy theory can be successfully applied to explain business students' motivation to use an ES in the bank loan decision context. Future ES research, based on the successful application of expectancy theory, could be fruitful in two areas. First, it could be used to examine the impact of previously researched factors/processes (e.g., education, cognitive style, management support, user participation, and user training) on motivation to use an ES by examining the impacts of these items on the models' elements (e.g., expectancies, instrumentalities, and second level outcome valences). Next, new research could provide for re-interpretation of previous research findings in the context of these models and their elements (Snead, 1988; Ronen and Livingstone, 1975).

ANNs are a promising method of predicting intended usage of a new ES in terms of predictive accuracy, adaptability, and robustness. This promise draws from three factors.

First, because human behaviors and judgements are better approximated by a nonlinear function than a linear function (Shepanski, 1983), ANNs will have better predictive accuracy than linear multiple regression models. Second, the ability to adaptively adjust the model is a virtue of ANNs, so ANNs respond swiftly to changes in the real world. Third, ANNs require neither any specific probability distribution or equal dispersion, nor do they demand rigid restriction on the use of input/output functions other than that they be continuous and differentiable. Thus ANNs have better robustness than the multiple regression approach (Tam & Kiang, 1992).

This study examined some behavioral factors which affect business students' motivation to employ an expert system to support loan decisions. Because human behavior and judgements are better approximated by a nonlinear function than a linear function (Shepanski, 1983), ANNs have better prediction accuracy than linear multiple regression models. The strong confirmation of the ANNs model's superiority in predicting the accuracy of business students' responses to ESs relative to the traditional multivariate techniques can provide ES developers, and indeed all of us who are interested in successful implementations of information systems, a more powerful measurement tool.

Business students as surrogates for managers has been well accepted in the MIS area since the Minnesota Experiments (Dickson, Senn, and Chervanny, 1977). However, because of multiple contexts and time frames, several researchers have questioned the adequacy of using students as surrogates for managers. Consequently, the surrogate issue has neither been settled nor have any universally recognized procedures or guidelines for surrogate use been developed (Hughes and Gibson, 1991). Therefore, additional evidence on the reasonableness of subrogation is needed. In this research, an attempt was made to evaluate the adequacy of the surrogation by analyzing differences between real bank loan officers and student surrogates in applying expectancy theory to estimate bank loan officers' motivation of maximum utilization of ES to the loan decision making.

The results of this research show that bank loan officers and business students are significantly different in valence and motivation levels. More specifically, business students revealed significantly higher valence levels and higher motivation levels to utilize ES than do bank loan officers. And the relative importance of the three second level outcome instrumentalities in evaluating each ES was different between business students and bank loan officers. More specifically, bank loan officers considered friendly relationship with customers as the most important factor to evaluate the attractiveness of ES, but business students considered the improvement of decision quality as the single most important factor to evaluate the attractiveness of ES. Furthermore, the relative importance of the valence and the expectancy for the bank loan officers were different from that of the business students. The bank loan officers placed higher weight on the expectation that their effort would be successful than on the perception of the attractiveness of implementation. In contrast, the business students placed a higher weight on the perception of the attractiveness of implementation than on the expectation that their effort would be successful. Thus, it appears in this context, that the loan officers exhibit more human-side qualitative characteristics in their business dealings than do college students who seem to be more oriented toward technology tools. This may be because of their various focuses of reference. Bank loan officers deal with customers on a daily basis whereas the students are placed in an artificial problem solving environment where technology is often the tool of choice to solve the problem. The result of this research can help to establish guidelines to assess the adequacy of using students as surrogates for managers, especially for expectancy theory research.

REFERENCES

Abdel-Khalik, R. A. (1974). On the efficiency of subject subrogation in accounting research. *The Accounting Review*, 49(4), 743-750.

Alderfer, C. P., & Bierman, H. (1970). Choices with risk: Beyond the mean and variance. *Journal of Business*. 43(3), 341-353.

Arnold, H. J., & Evans, M. G. (1979). Testing multiplicative models does not require ration scales. *Organizational Behavior and Human Performance*, 24(1), 41-59.

Ashton, R., & Kramer, S. S. (1980). Students as surrogates in behavioral accounting research: Some evidence. *Journal of Accounting Research*, 18(1), 1-13.

Barki, H. & Huff, S.L. (1985). Change, attitude to change, and decision support system success. *Information and Management*, 9(5), 261-268.

Batlis, N., & Waters, L. (1973, Winter). Locus of control and achievement motivation as moderators of the expectancy-academic performance relationship. *Educational and Psychological Measurements*, pp. 895-902.

Brunett, J. J., & Dunn, P. M. (1986). An appraisal of the use of student subjects in marketing research. *Journal of Business Research*, 14(4), 329-343.

Butler, J., & Womer, K. (1985). Hierarchical vs. non-nested tests for contrasting expectancy valence models: Some effects of cognitive characteristics. *Multivariate Behavioral Research*, 20(3), 335-352.

Cerveny, R. P., & Sanders, L. G. (1986). Implementation and structural variables. *Information & Management*, 11(2), 191-198.

Churchill, G. A., & Suprenant, C. (1982). An investigation into the determinants of customer satisfaction. *Journal of Marketing Research*, 19(11), 491-504.

Cronbach, L. J. (1951, September). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16, pp. 297-334.

Davis, L. R. (1987). Expert systems for accounting: Has their time come? *Journal of Accountancy*, 160(9), 126-148.

Dickson, G. W., Senn, J. A., & Chervany, N. L. (1977). Research in management information systems: The Minnesota experiments. *Management Science*, 23(9), 913-923.

Dillard, J. (1979). Valence-instrumentality-expectancy theory model validation using selected accounting groups. *Accounting, Organization and Society*, 4(3), 179-186.

Dipboye, R. L., & Flanagan, M. F. (1979). Research settings in industrial and organizational psychology: Are findings in the field more generalizable than in the laboratory? *American Psychologist*, 34(1), 141-150.

Dobbins, G. H., Lane, I. M., & Steiner, D. D. (1988). A note on the role of laboratory methodologies in applied behavioral research: Don't throw out the baby with the bath water. *Journal of Organizational Behavior*, 9(3), 281-286.

Emory, W. C., & Cooper, D. R. (1991). *Business Research Methods (4th ed.).* Homewood, IL: Irwin.

Ferris, K. (1977). A test of the expectancy theory of motivation in the accounting environment. *The Accounting Review*, 52(3), 605-615.

Ferst, W. L., & Cheney, P. H. (1982). Factors affecting the perceived utilization of computer-based decision support systems in the oil industry. *Decision Sciences*, 13(4), 554-569.

Fusilier, M. R., Ganster, D. C., & Middlemist, R. D. (1984). A within-person test of the form of the expectancy theory model in a choice context. *Organizational Behavior and Human Performance*, 34(2), 323-342.

Ginzberg, M. J. (1980). An organizational contingencies view of accounting and information systems implementation. *Accounting, Organizations, and Society*, 5(4), 369-382.

Goodall, A. (1985). *The guide to expert systems.* New Jersey: Learned Information.

Gordon, M. E., Slade, A. L., & Schmitt, N. (1986). The science of the sophomore revisited: From conjecture to empiricism. *Academy of Management Review*, 11(1), 191-207.

_____________, Slade, A. L., & Schmitt, N. (1987). Student guinea pigs: Porcine predictors and particularistic phenomena. *Academy of Management Review*, 12(1), 160-163.

Greenberg, J. (1987). The college sophomore as guinea pig: Setting the record straight. *Academy of Management Review*, 12(1), 157-163.

Greenhaus, J. H., Sagalski, T., & Crispin, G. (1978). Relationships between perceptions of organizational size and the organizational choice process. *Journal of Vocational Behavior*, 13(1), 113-125.

Griffin, L., & Harrell, A. M. (1991). An empirical examination of managers' motivation to implement just-in-time procedures. *Journal of Management Accounting Research*, 3(3), 98-112.

Hall, F. S., & Hall, D. T. (1976). Effects of job incumbents' race and sex on evaluation of managerial performance. *Academy of Management Journal*, 19(1), 476-481.

Harlan, A., Kerr, J., & Kerr, S. (1977). Preference of motivator and hygiene factors in a hypothetical interview situation: Further findings and some implications for the employment interview. *Personal Psychology*, 30(3), 557-566.

Harmon, P., & King, D. (1985). *Expert Systems.* New York: Wiley Press.

Harrell, A. M., & Stahl, M. J. (1984). Modeling managers' effort-level decision for a within-persons examination of expectancy theory in a budget-setting. *Decision Sciences*, 15(1), 52-73.

______________, Caldwell, C., & Doty, E. (1985). Expectancy theory predictions of accounting students' academic success motivation. *The Accounting Review*, 60(4), 724-735.

Harvey, J. J. (1987). Expert systems: Present and future. *Computers and People*, 36(1), 109-123.

Hecht-Nielson, R. (1987). Counterpropagation networks. *Applied Optics*, 26(23), 4979-4984.

Henson, R. (1976). Expectancy beliefs, ability, and personality in predicting academic performance. *Journal of Educational Research*, 70(1), 41-44.

Hughes, C. T., & Gibson, M. L. (1991). Students as surrogates for managers in a decision-making environment: An experimental study. *Journal of MIS*, 8(2), 153-166.

Jarvenpaa, S. L., Dickson, G. W., & DeSantis, G. (1985). Methodological issues in experimental IS research: Experiences and recommendations. *MIS Quarterly*, 9(2), 141-156.

Jiambalvo, J. (1979). Performance evaluation and directed job effort: Model development and analysis in a CPA firm setting. *Journal of Accounting Research*, 17(2), 436-455.

Jung, J. D. (1991). *An empirical study on perceived importance of systems analysts' job skill and their relationship with information systems effectiveness*. Unpublished Ph.D. dissertation, Mississippi State University.

Kennedy, C. W., Fossum, J. A., & White, B. J. (1983). An empirical comparison of within-subjects and between-subjects expectancy theory models. *Organizational Behavior and Human Performance*, 32(1), 124-143.

Kren, L. (1990). Performance in a budget-based control system: An extended expectancy theory model approach. *Journal of Management Accounting Research*, 2(3), 100-112.

Lawler, E. E., III., Kuleck, W. J. Jr., Rhode, J. G., & Sorenson, J. E. (1975). Job choice and post decision dissonance. *Organizational Behavior and Human Performance*, 13(1), 133-145.

Leonard-Barton, D., & Svioka, J. J. (1988). Putting expert systems to work. *Harvard Business Review*, 66(2), 91-98.

Lovata, L. M. (1987). Behavioral theories relating to the design of information systems. *MIS Quarterly*, 11(2), 147-149.

Lucas, H. C. (1978). Empirical evidence for a descriptive model of implementation. *MIS Quarterly*, 2(2), 27-41.

Mai-Dalton, R. R. & Sullivan, J. J. (1981). The effects of managers' sex on the assignment to a challenging or a dull task and reasons for the choice. *Academy of Management Journal*, 24(3), 603-612.

Mitchell, T. R., & Knudsen, B. W. (1973). Instrumentality theory predictions of students' attitude toward business and their choice of business as an occupation. *Academy of Management Journal,* 16(1), 41-52.

_______________, & Nebeker, D. M. (1973). Expectancy theory prediction of academic effort and performance. *Journal of Applied Psychology,* 57(1), 61-67.

Matsui, T., & Ikeda, H. (1976). Effectiveness of self-generated outcomes for improving prediction in expectancy theory research. *Organizational Behavior and Human Performance,* 17(1), 289-298.

Muchinsky, P. M. (1977). A comparison of within- and across- subjects analyses of the expectancy-valence model for predicting effort. *Academy of Management Journal,* 20(1), 154-158.

_______________, & Taylor, M. S. (1976). Intrasubject predictions of occupational preference: The effect of manipulating components of the valence model. *Journal of Vocational Behavior,* 8(1), 185-195.

Oldham, G. R. (1976). Organizational choice and some correlates of individual expectancies. *Decision Sciences,* 7(4), 873-884.

Oz, E. (1990). The attitude of managers-to-be towards software piracy. *OR/MS Today,* 17(4), 24-26.

Park, C. W. & Lessig, V. P. (1977). Students and housewives: Differences in susceptible to reference group inference. *Journal of Consumer Research,* 4(2), 102-110.

Philip, G. C., & Schultz, H. K. (1990). What's happening with expert systems? *AI Expert,* 5(11), 57-59.

Plath, D. A. & Kloppenborg, T. J. (1989). Do expert systems help make better lending decisions? *Journal of Retail Banking,* 11(4), 27-37.

Polczynski, J. & Shirland, L. (1977). Expectancy theory and contract grading combined as an effective motivation force for college students. *Journal of Educational Research,* 70(5), 238-241.

Ravichandran, R., Baker, D. D., & Randall, D. M. (1989). Linear and nonlinear valence functions: A behavioral decision-making assessment. *Decision Sciences,* 20(4), 685-699.

Remus, W. (1986). Graduate students as surrogates for managers in experiments on business making. *Journal of Business Research,* 14(1), 19-25.

Robbins, S. P. (1991). *Management (3rd ed.).* New Jersey: Prentice-Hall.

Robey, D. (1979). User attitudes and management information system use. *Academy of Management Journal,* 22(3), 527-538.

Robbins, S. P. (1991). *Management (3rd ed.).* New Jersey: Prentice-Hall.

Rosen, B. & Jerdee, T. H. (1973). The influence of sex-role stereotypes on evaluation of male and female supervisory behavior. *Journal of Applied Psychology*, 57(1), 44-48.

Rumelhart, D. E., McClelland, J., & the PDP Research Group (Eds.). (1986). *Parallel distributed processing explorations in the microstructure of cognition.* MA: MIT Press.

Rynes, S., & Lawler, J. A policy-capturing investigation of the role of expectancies in the decision to pursue job alternatives. (1983). *Journal of Applied Psychology,* 68(4), 620-631.

Schmidt, F. (1973). Implications of measurement problems for expectancy theory research. *Organizational Behavior and Human Performance*, 10(2), 243-251.

Schmitt, N., & Son, L. (1981). An evaluation of valence models of motivation to pursue various post high school alternatives. *Organizational Behavior and Human Performance*, 27(1), 135-150.

Schwab, D. J., Olian-Gottlieb, Heneman, H. (1979). Between subjects expectancy theory research: A statistical review of studies predicting effort and performance. *Psychological Bulletin*, 86(1), 139-147.

Shepanski, A. (1983). Tests of theories of information processing behavior in credit judgement. *Accounting Review,* 58(2), 581-599.

Smith, R., Ascough, J., & Ettinger, R. (1976). The relationship between expectancy of success and task difficulty as a function absolute and relative success criteria. *Social Behavior and Personality,* 13(2), 277-282.

Snead, K. C. (1991). An application of expectancy theory to examine managers' motivation to utilize a decision support system. *Journal of Management Accounting Research,* 3(3), 213-222.

Stahl, M. J., & Grigsby, D. W. (1987). A comparison of unit, subjective, and regression measures of second-level valences in expectancy theory. *Decision Sciences,* 18(1), 62-72.

__________, & Harrell, A. M. (1981). Modeling effort decisions with behavioral decision theory: Toward an individual differences model of expectancy theory. *Organizational Behavior and Human Performance*, 27(3), 303-325.

__________, & Harrell, A. M. (1983). Using decision modeling to measure second level valences in expectancy theory. *Organizational Behavior and Human Performance,* 32(1), 23-34.

Swieringa, R. & Weick, K. (Supplement 1982). An assessment of laboratory experiments in accounting. *Journal of Accounting Research*, 20, 56-101.

Stylianou, A. C., Madey, G. R., & Smith, R. D. (1992). Selection criteria for expert system shells: A socio technical framework. *Communications of the ACM,* 35(10), 30-48.

Tam, K. Y. & Kiang, M. Y. (1992). Managerial applications of neural networks: The case of bank failure predictions. *Management Science*, 38(7), 926-947.

Thompson, D. M., & Martin, J. S. (1990). Expert systems in banking. *PC AI*, 4(3), 28-33.

Turban, E. (1993). *Decision support and expert systems: Management support systems (3rd ed.).* New York: Macmillan Publishing Company.

Vroom, V. C. (1964). *Work and motivation.* New York: Wiley.

Wahba, M. A., & House, R. J. (1974). Expectancy theory in work and motivation: Some logical and methodological issues. *Human Relations*, 27(2), 121-147.

Waterman, D. A. (1985). *A guide to expert systems.* MA: Addison-Wesley.

Wheeler, K. G., & Mahony, T. A. (1981). The expectancy model in the analysis of occupational choice. *Journal of Vocational Behavior*, 19(1), 113-122.

Zawa, S. (1991). Knowledge based systems in the state bank of new south wales. *The World Congress on Expert Systems Proceedings*, 1, 706-712.

Zedeck, S. (1977). An information processing model and approach to the study of motivation. *Organizational Behavior and Human Performance*, 26(1), 47-77.

Zimmer, I. (1980). A lens study of the prediction of corporate failure by bank loan officers. *Journal of Accounting Research*, 18(2), 629-636.

Zurada, J. M. (1992). *Introduction to artificial neural systems.* MN: West Publishing.