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Vroom의 Expectancy Theory에 의한 은행 매니저들의 전문가 시스템 사용에 대한 모티베이션 분석

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An Application of Vroom's Expectancy Theory to Examine Bank Managers' Motivation to Utilize an Expert System

Expert Systems (ES) have been successfully applied to bank loan decisions. However, with regard to bank loan decisions, most loan officers approach the acquisition of an ES with apprehension, which implies that organizational resources devoted to the development and implementation of ES may have been wasted or misused. Because the primary cause of the users resistance to use ES are more significantly related to the behavioral elements rather than technical elements, applying appropriate behavioral theory to the well representative sample group of the whole bank loan officers in the United States with a very accurate measurement tool can provide some clues for developing successful ES for bank loan officers. In this study : 1) Vroom's (1964) expectancy theory was selected to explain bank loan managers' motivation to use an ES ; and 2) the ANN model's prediction power to estimate bank loan officers' motivation levels of using an ES was examined.

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I. INTRODUCTION

Up to now, the most successful Artificial Neural Networks(ANNs) application areas in business environment have been: firm bankruptcy prediction under a variety of different problem settings(Wilson and Sharda, 1993;Tam and Kiang, 1992); corporate bond rating prediction(Dutta and Sherkhar, 1988;Utans and Moody, 1991;Surkan and Singleton, 1990);credit card fraud prevention(Rochester, 1990; Marose, 1990);stock exchange(Kamijo and Tanigawa, 1989);bank signature validation(Francett, 1989). Almost every application has been focused toward financial or quantitative aspects. However, this study provides an early approach to examine human behavior and qualitative decision making with ANNs. More specifically, in this research, ANNs are used to predict bank managers' motivation to use Expert Systems(ES).

ES are considered one of the most successful branches of Artificial Intelligence (AI)(Stylianou et al., 1992). Along with many other application areas, ES have been successfully applied to bank loan decisions(Thompson and Martin, 1990). However, there is the persistent gap between the ability to develop new ES technology and the ability effectively use it (Turner, 1982). Although successful implementations of ES are very important, two factors have led to their failure in the past (Plath and Kloppenborg, 1989). First, unrealistic implementation success expectations maintained by users has dictated that implementations were doomed to failure before their birth. Next, managerial mistakes in attempting to implement this new technology in a business environment have led to unsatisfactory results in many instances. As a consequence, the vast potential which ES offer to bank managers has not been consistently translated into demonstrated business performance. Because of the problem, bankers have become increasingly skeptical regarding the claims of ES advocates. For example, a survey reports that 36% of respondents stated that most loan officers in their banks approach 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 bank managers' motivation to use an ES in a bank loan decision context.

II. THEORETICAL BACKGROUND AND SUPPORTING LITERATURES

1. Implementation Research

Studies which examine an information system's successful implementation fall into two major streams : implementation factor research and implementation process research(Ginzberg, 1980;Lucas, 1981; Cerveny and Sanders, 1986).

A major concern related to the implementation factor research is to identify factors which can impact on intended system usage. The characteristics of the user, the system, and the organization are common categories of those factors(Fuerst and Cheney, 1982;Snead, 1988).

Implementation process research tries to find out how the quality of the implementation process impacts on intended system usage. Management support, user involvement, and user training are typical implementation process variables(Lucas, 1981; Snead, 1988).

Few conclusions can be drawn from the implementation factor stream of research (Cerveny and Sanders, 1986;Snead, 1988). While some factors have been found to be associated with implementation success in one or more studies, their significant relationship with implementation has not been consistently demonstrated across studies. Nicholas(1981) notes that Ginzberg's review of factor studies also revealed poor generalizability of results. In fact, the work of Fuerst and Cheney(1982) appears to be motivated by the mixed results of research with respect to user, system, and organizational factors significantly impacting MIS implementation.

As with implementation factor research, few consistent and generalizable findings have emerged from the implementation process stream of process. While Ginzberg (1981) notes only management support and user involvement have been consistently found to be important determinants of implementation success, he subsequently found no empirical support for user involvement. Inconsistent results are found between Fuerst and Cheney's(1982) and Sanders and Courtney's(1985) research. Although Fuerst and Cheney(1982) found that only user training emerged as an important implementation process variable, Sanders and Courtney(1985) found that top management support, user training, and length of system use are important implementation process variables(Snead, 1988). A part of the inconsistent results may be because research in the implementation area(and corresponding inconsistent results) has failed to rely on behavioral theory. Research in implementation research tends to underutilize existing knowledge in behavioral theory and produces few consistent and generalized conclusions(Snead, 1991;Lovata, 1987;Ginzberg, 1980;Robey, 1979).

Because of users' tendency, in response to questions, to request more information than is necessary to solve a problem (Dermer, 1973), in addition to simply asking users, designers need another basis for determining a decision maker's responses to new systems(Lovata, 1987). Among several behavioral theories, which suggest how users will react to various types of information, Vroom's(1964) expectancy theory has been the most widely accepted over the past several decades(Griffin and Harrell, 1991;Snead, 1988;Locke, 1975; Mitchell 1979;Stahl and Harrell, 1983; Wahba and House, 1974;Arnold, 1981; House, Shapiro and Wahba, 1974;Pecotich and Churchill, 1981;Lawler, 1973).

2. Expectancy Theory

Vroom's(1964) 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 to the individual(Robbins, 1991). Vroom's(1964) expectancy theory involves two models: the valence model and the force model.

2-1. 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 :

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

where :

V_j=the attractiveness(valence) for an end-user to make maximum usage of a newly developed ES(first level outcome).

V_k=the attractiveness(valence) of second level outcomes associated with ES use.

I_{jk}=the likelihood that, if an ES is maximally used by an end-user, 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. 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).

2-2. 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 Vroom's (1964) relationship equation is :

$$F_i = V_j E_{ij} \qquad (2)$$

where :

F_i=an end-user's motivation(effort) to make maximum use of a new ES.

V_j=the valence associated with maximum ES use.

E_{ij}=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.

2-3. Across-persons vs. Within-persons Methodologies

Conventional expectancy theory employed across-persons methodologies(Ferris, 1977 ; Dillard, 1979 ; Jiambalvo, 1979 ;

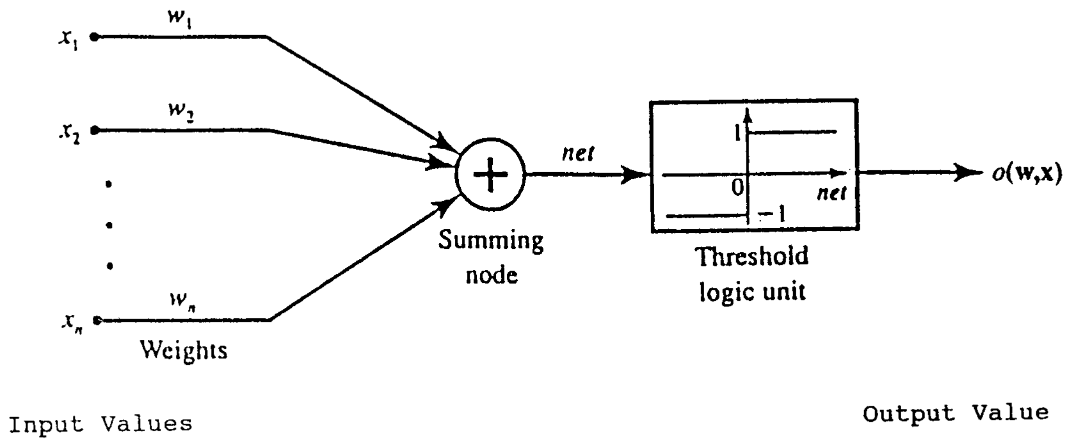
Wahba and House, 1974 ; Schwab, Olian-Gottlieb and Heneman, 1979 ; Batlis and Waters, 1973 ; Smith, Ascough and Ettinger, 1976 ; Henson, 1976 ; Polczynski and Shirland, 1977). However, this across-persons approach generally provided relatively low predictive ability regarding motivation. Based on a large number of reviews of these studies, Mitchell(1974) reported an average coefficient of determination(R2) of only 27 percent for the force model's predictions of motivation.

As a result, the use of an across-persons methodology for expectancy theory has been severely criticized on measurement and methodological grounds(Mitchell and Beach, 1977;Zedeck, 1977;Wolf and Connolly, 1981;Kopelman, 1977;Schmidt, 1973). Koplelman(1977) emphasized that the across-persons approach is not the correct method because expectancy theory is formulated on a within-persons basis. Wolf and Connolly(1981) also criticized the across-person approach, stating : "The core objections to these between-subjects analyses, then, is that they have neither theoretical nor practical significance"(1981, p.43). Schmidt(1973) pointed out that, if a correlation test is used, the frequently-used Likert scales, when multiplied, may produce inconsistent tests of the theory. Campbell and Stanley(1963) insisted that the across-persons approach can mask variations within individuals, therefore such studies lack internal validity. According to Kennedy et al. (1983), the advantage of the within-persons approach is individual differences on aspects such as ability, experience, wealth, and opportunity costs(job related pressure), can be eliminated.

Mitchell and Beach(1977) and Zedeck (1977) proposed use of the judgement modeling approach, which was frequently employed to examine cognitive issues (Ashton, 1982;Libby, 1981), to within-persons expectancy theory. In response to the proposal, Stahl and Harrell(1981, 1983) used decision modeling for a within-persons examination of expectancy theory. In this research, within-persons approach was employed.

3. 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. Furthermore, previous expectancy theory researches mainly use multiple regression and multiple discriminant techniques for analysis. However, before applying those multivariate techniques, many assumptions such as normality, homoscedasticity, and linearity must be examined. Therefore the research results can only be justified when the data used for the research satisfies those assumptions. However, most of the business research have problems to satisfy those assumptions. Because in the bususiness research, the most popular scaling method is Likert scale(Emory and Cooper, 1991), and the Likert-type scale has problems related to normality and homoscedasticity. To solve those normality and homoscedasticity problems, ANNs model approach is employed in this research, because ANNs model does not assume any probability distribution or equal dispersion(Tam and Kiang, 1992). Therefore, application of an ANN model approach to improve prediction power of endusers' motivation to use ES can solve many of the previously cited problems.



$$\text{If } \sum_{i}^{n} W_i X_i \geq \text{Threshold, Output value} = 1$$

$$\text{If } \sum_{i}^{n} W_i X_i < \text{Threshold, Output value} = -1$$

Source: Zurada, J. M. (1992). Introducing to artificial neural systems. Saint Paul, MN: West Publishing (p. 36).

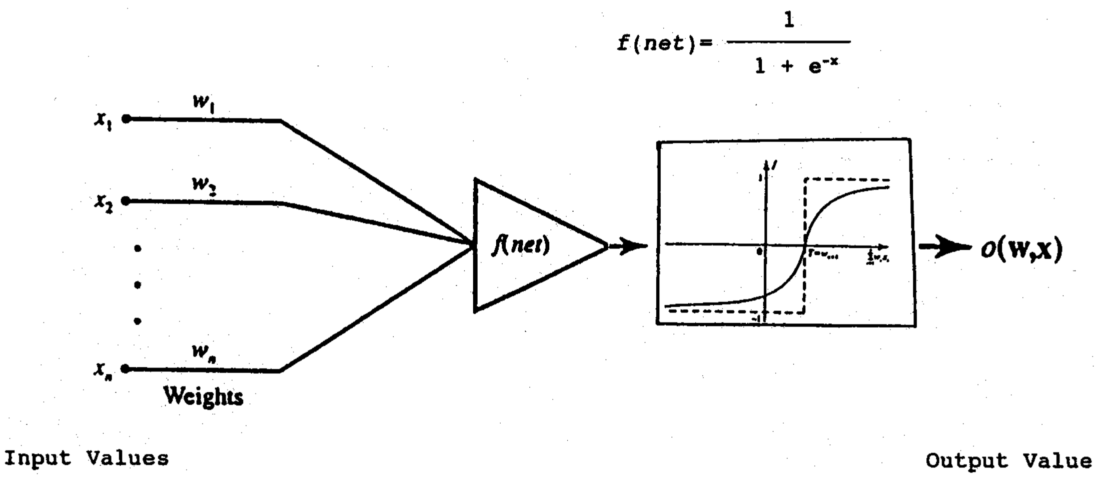
Figure 1. A Hard-Limiting Neuron(Binary Perceptron)

An ANN consists of a number of highly interconnected simple processing units. ANNs emulate parallel processing inspired by models of the human brain and nerve cells. The basic processing elements of ANNs are called(artificial) neurons, units, or nodes. Neurons are often organized in layers, and connected to other neurons in adjacent layers. Each connection strength is expressed by a numerical value called a weight. A neuron computes a weighted sum of its inputs from other units, called net input value or activation level. The net input value will be transformed to generate a reasonable output value(e.g., between zero and one). The simplest transform function is using a binary threshold unit. In this case, if the net input exceeds a certain bias level, called a threshold, the neuron will be fired. McCulloth and Pitts (1943) formulated a highly simplified model of a neuron as a binary threshold unit. The McCulloch—Pitts model diagram is shown in Figure 1.

However, the most popular nonlinear transform function is a sigmoid function (or logical activation function), and an example of the sigmoid function equation is

$$f(x) = \frac{1}{1 + e^{-x}}$$

A diagram of typical model, which employs the sigmoid function is shown in Figure 2.



Source: Zurada, J. M. (1992). Introduction to artificial neural systems. Saint Paul, MN: West Publishing (p. 36).

Figure 2. A Soft—Limiting Neuron(Continuous Perceptron)

Although current single processor computers, based on the John von Neumann design, outperform ANNs for tasks based on precise and fast arithmetic operations, ANNs represent a promising new generation of information processing networks. Because of the architectural difference, ANNs can be distinguished from traditional single processor computers in the following aspects.

1) ANNs have high fault–tolerance.
2) ANNs are retrainable, not programmable.
3) ANNs can deal with fuzzy, incomplete, probabilistic, noisy, or inconsistent information.
4). ANNs are adaptive(flexible) to a new environment.
5) ANNs are domain–independent(general–purpose problem solvers)(Dayhoff, 1990 ; Hertz et al., 1991).

Currently, more than one hundred different neural network models and algorithms have been developed and studied. Among them, the thirteen most important ANNs architectures are summarized in Table 1.

Those ANNs can be categorized in terms of two aspects : recall of information modes and learning modes. First, according to the recall modes, the ANNs can be classified into feedforward networks and feedback networks. In the feedforward mode, the recall of information can be performed from input toward output only, and has no memory. Recall in such a network is instaneous, thus the network's behavior depends on what happens now rather than what happened in the past. Therefore the network responds to its present input. The second group of networks recall information with feedback operational computation, and are called feedback networks or recurrent. These networks can be considered as dynamic systems, and a certain time interval is needed for their recall to be completed through the interaction between input and output. Second, according to the learning modes, the ANNs can be classified into supervised learning and unsupervised learning(Lippman, 1989). In supervised learning, ANNs are presented with target outputs for each input pattern. In unsupervised training, ANNs adjust their weights in response to input patterns without the benefit of target answers.

Many algorithms have been developed to train ANNs. The algorithms can be classified into supervised learning algorithms and unsupervised learning algorithms. Important algorithms for supervised learning are : Perceptron(Rosenblatt, 1958), Widrow−Hoff(Widrow, 1962), Correlation (Kohonen, 1974), Outstar(Grossberg, 1977, 1982), and back−error propagation (Delta)(Rumelhart, McClelland, et al., 1986) ; Rumelhart, Hinton, and Williams, 1986) learning rules. Hebbian(Hebb, 1949) and Winner−take−all(Hecht−Nielson, 1987) learning rules are important algorithms for unsupervised training.

Table 1. Classification of the Most Important ANNs According to Their Learning and Recall Modes

Network Architecture	Learning Mode* S, U, R	Recall Mode** FF, REC
Single−layer Network of Discrete and Continuous Perceptrons	S	FF
Multilayer Network of Discrete and Continuous Perceptrons	S	FF
Gradient−type Network	R	REC
Linear Associative Memory	R	FF
Autoassociative Memory	R	REC
Bidirectional Associative Memory (also Multidirectional Associative memory)	R	REC
Temporal Associative Memory	R	REC
Hamming Network	R	FF
MAXNET	R (fixed)	REC
Clustering Network	U	FF
Counterpropagation Network	U	FF
Self−Organizing Neural Array	U	FF
Adaptive Resonance Theory 1 Network	U	REC

*
S−Supervised
U−Unsupervised
R−Recording(Batch)

**
FF−Feedforward
REC−Recurrent

Adapted from Zurada, J. M. (1992). Introduction to artificial neural systems. Saing Paul, MN : West Publishing (p. 75).

Among them, back－error propagation leaning, or more commonly, backpropagation is the most successful and one of the most studied learning algorithm in the neural network arena(Hecht and Nielsen, 1990). Therefore, back－error propagation will be used for this research. Back－error propagation is considered a multilayer network, and classified into a feed forward mode and a supervised learning mode(Turban, 1993).

3－1. Back－Error Propagation

Typical back－error propagation consists of three or more layers of processing units. The topology for a typical three－layer back propagation network is shown in Figure 3.

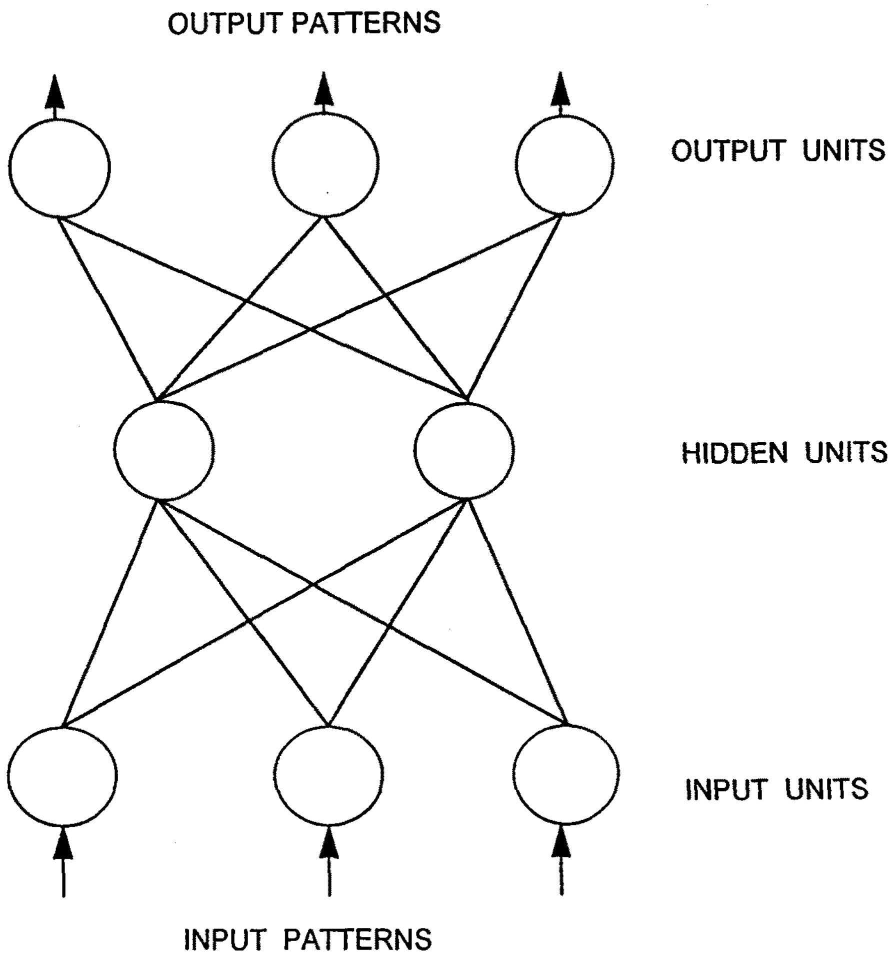


Figure 3. A Two－Layered Back－Propagation Network, Fully Interconnected

The input layer is the bottom layer of units. ANNs receive external input through the input layer. The output layer is located at the top. ANNs' responses are determined at the output layer. The hidden layer is located between the input layer and the output layer. It serves to help perform the desired mapping between an input and its corresponding output. The layers in Figure 3 are fully interconnected. The back-error propagation learning algorithm consists of a forward-propagating step and a backward-propagating step(Dayhoff, 1990;Hertz et al., 1991; Tam and Kiang, 1992).

III. HYPOTHESES DEVELOPMENT

This section presents the development of the four hypotheses that are tested in this research. The hypotheses are grounded in motivation behavior through expectancy theory. The first hypothesis examines in this study is whether the valence of expectancy theory can be used to examine the motivation of a bank loan manager to employ an ES. Therefore, H1 in alternative form is :

H1 : A loan manager's perception of the attractiveness of using an ES to the job can be well explained by the valence model.

The second hypothesis is to test the force model. That is :

H2 : A loan manager's motivation to use an ES to the job can be well explained by the force model.

Successful verification of H1 and H2 means that Vroom's expectancy theory can be used to predict a user's motivation to use an ES.

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. 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. Therefore, H3 and H4 in alternative form are :

H3 : A loan manager's perception of the attractiveness of employ an ES to the job can be more accurately predicted by ANN model than multiple regression.

H4 : A loan manager's motivation to

employ an ES to the job can be more accurately predicted by ANN model than multiple regression.

Ⅳ. RESEARCH METHODOLOGY

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

Sample subjects were United States bank loan managers. A mail questionnaire survey was used to collect loan managers' motivation to use an ES in loan making decisions. The sampling frame was the Polk's Bank Directory(1994), which provides an alphabetical list of over 10,000 bank loan managers. 1,000 bank loan managers were selected by a systematic sampling from the mailing list available.

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 is incorporated into the valence model. The three second—level outcomes(Ijk) and the expectancy variable(Eij) are presented at two levels of likelihood(10 percent and 90 percent). Therefore, 16(24) 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 secondlevel outcomes(Vk 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 7point Likert scale was employed with 1= very unattractive and 7= very attractive.

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 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)

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 effortlevel decision was used to measure motivational force F_i in Equation 2.

PART Ⅲ of the questionnaire was designed to gather demographic information.

Ⅴ. DATA ANALYSIS

Out of the 1,000 bank loan managers who were selected from Polk's Bank Directory (1994) to receive the mail survey,

Table 2. Demographics of Respondents — Bank Loan Officers(n = 150)

A. Sex	
Male	137(91.3%)
Female	13(8.7%)
B. Age	
Under 30	9(6.0%)
30 – Under 40	46(30.7%)
40 – Under 50	61(40.7%)
50 – Under 60	26(17.3%)
60 and over	8(5.3%)
C. Highest Academic Degree Received	
High school graduate	22(14.7%)
Bachelors	90(60.0%)
Masters	38(25.3%)
Doctorate	0(0.0%)
D. years Working for Current Organization	
Less than 3 years	27(18.0%)
3 – less than 8 years	49(32.7%)
8 years and over	74(49.3%)
E. Years of Experience Marking Loan Decisions	
Less than 3 years	6(4.0%)
3 – less than 8 years	21(14.0%)
8 years and over	123(82.0%)
F. Size of Bank Total Assets (As of August 15, 1993)	
Less than \$ 100 millions	103(68.7%)
\$ 100 millions – less than \$ 1 billion	36(24.0%)
\$ 1 billion – less than \$ 10 billions	10(6.7%)
\$ 10 billions and above	1(0.7%)

164 responded. Fourteen responses were excluded because of incomplete questionnaires, thus 150 (15.0 percent) complete and usable responses are included in the data analysis. The 15.0 percent response rate is believed to be a function of the bank loan managers' unfamiliarity to the ES concept and/or because of the complexity of the questionnaire, however it achieves reported national averages of 15% (Jeong, 1991). The demographics of the bank loan managers are summarized in Table 2.

1. Nonresponse Bias Test

To examine nonresponse bias, the total assets of responding and non—responding banks were used in a Chisquare goodness-offit test. The distribution of the total assets of banks in the U.S. was available through the Thompson Bank Directory : United States (1994). Based on the Chisquare test for responding and nonresponding banks' total assets, there is no evidence of nonresponse bias.

2. Reliability Test

For reliability test, Cronbach's (1951) alpha was examined for both individual items and overall measures. The results are reported in Table 3. These values are well above the minimum acceptable value of 0.7 (Churchill and Suprenant, 1982).

3. Validity Tests

For the valence model's construct validity test (PART I and DECISION A), the ANOVA test for the factorial experiments was used. The ANOVA test results are summarized in Table 4. For the force model's construct validity test (PART II and DECISION B), nonparametric multiple discriminant analysis was used. The test results are summarized in Table 5 and verify construct validity.

4. Results of Analyses Employed to Examine H1

H1 suggests the applicability of the valence model of expectancy theory for a loan manager's perception of the attractiveness of using an ES in the bank loan decision context. As mentioned earlier, this research uses within—persons approach. Within—persons methodology for expectancy theory was developed by Stahl and Harrell (1981, 1983).

The theoretical basis of the within—per-

Table 3. Reliability Coefficients

	Item	Alpha
PART I	Product 1	0.776282
	Product 2	0.774535
	Product 3	0.769723
	Product 4	0.774273
	Product 5	0.758811
	Product 6	0.782068
	Product 7	0.770755
	Product 8	0.775552
PART II	Product A	0.768546
	Product B	0.772618
	Product C	0.774583
	Product D	0.760838
	Product E	0.769566
	Product F	0.759134
	Product G	0.765770
	Product H	0.760704
	Product I	0.769426
	Product J	0.763742
	Product K	0.768940
	Product L	0.766353
	Product M	0.755832
	Product N	0.771137
	Product O	0.778612
	Product P	0.776144
	Cronbach Alpha	0.777378

Table 4. The Result of Factorial Experiment ANOVA For Valence Model

Source	DF	Anova SS	Mean Square	F Value	Pr > F
CO	1	635.107500	635.107500	428.84	0.0001
FR	1	1010.167500	1010.167500	682.09	0.0001
DZ	1	1649.707500	1649.707500	1113.93	0.0001
CO*FR	1	4.687500	4.687500	3.17	0.0755
CO*DQ	1	0.042230	0.042230	0.04	0.8473
FR*DQ	1	0.285473	0.285473	0.25	0.6165
CO*FR*DQ	1	4.055743	4.055743	3.57	0.0594

TABLE 5. The Result of MDA with Nonparametric Option For Force Model

Pooled Within – Class Correlation Coefficients / Prob > | R |		
Variable	VA	EX
VA	1.00000	−0.51181
	0.0	0.0001
EX	−0.51181	1.00000
	0.0001	0.0

Between – Class Correlation Coefficients / Prob > | R |		
Variable	VA	EX
VA	1.00000	0.91437
	0.0	0.0039
EX	0.91437	1.00000
	0.0039	0.0

Total – Sample Correlation Coefficients / Prob > | R |		
Variable	VA	EX
VA	1.00000	0.00000
	0.0	1.0000
EX	0.00000	1.00000
	1.0000	0.0

Statistic	Value	F	Num DF	Den DF	Pr > 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	1098.061	6	2989	0.0

sons approach is comparing an individual's motivation measurement under one set of circumstances to that same individual's motivation measurements under differing sets of circumstances (Griffin and Harrell, 1991). Multiple regression has been the most popular analysis technique for the withinperson's approach of expectancy theory (Schmitt, 1973 ; Arnold and Evans, 1979 ; Baker and et al., 1988 ; 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, 1988). In the within–persons approach, individual regression models are established for each sample subject. In this study, to test H1, 150 regression models should be established corrosponding to the 150 research subjects. 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.

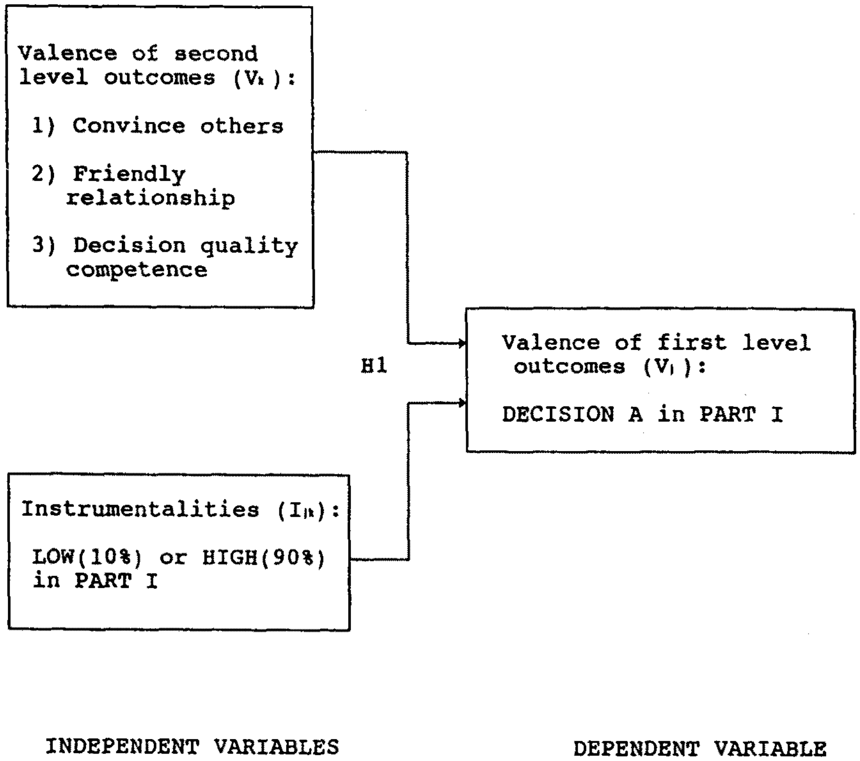


Figure 4. Diagram for the Relationship of Hypothesis 1

The valence regression model used to test H1 is :

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

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 maximum 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

Based on the results, at the=0.1 level(i.e., p-values were less than 0.1), all of the models achieved significance. Therefore, at the=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 6 presents summary information of the regression data analysis, and provides a composite, for all 150 valence models', mean R^2, mean β values, standard deviations and range values. From the table, the mean R^2 of 0.9048 is further evidence of strong support for hypothesis H1.

Table 6. Summary of Within-persons Valence Regression Models

	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

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 quality

5. Results of Analyses Employed to Examine H2

Hypothesis H2 suggests the applica-bility of Vroom's (1964) force model of expectancy theory for an enduser's motivation to use ES in the bank loan decision context.

Because the analysis required for testing H2 is very similar to the analysis required for examination of H1, similar within-persons multiple regression analysis approach was used to test H2. The dependent variable was the motivation measure obtained by the decisions in DECISION B, and the independent variables were the perceived attractiveness of the first level outcome of maximum ES use (DECISION A) and the expectancy (probability) that effort to use the ES to the maximum extent will be successful(PART II). Figure 5 shows the relationship.

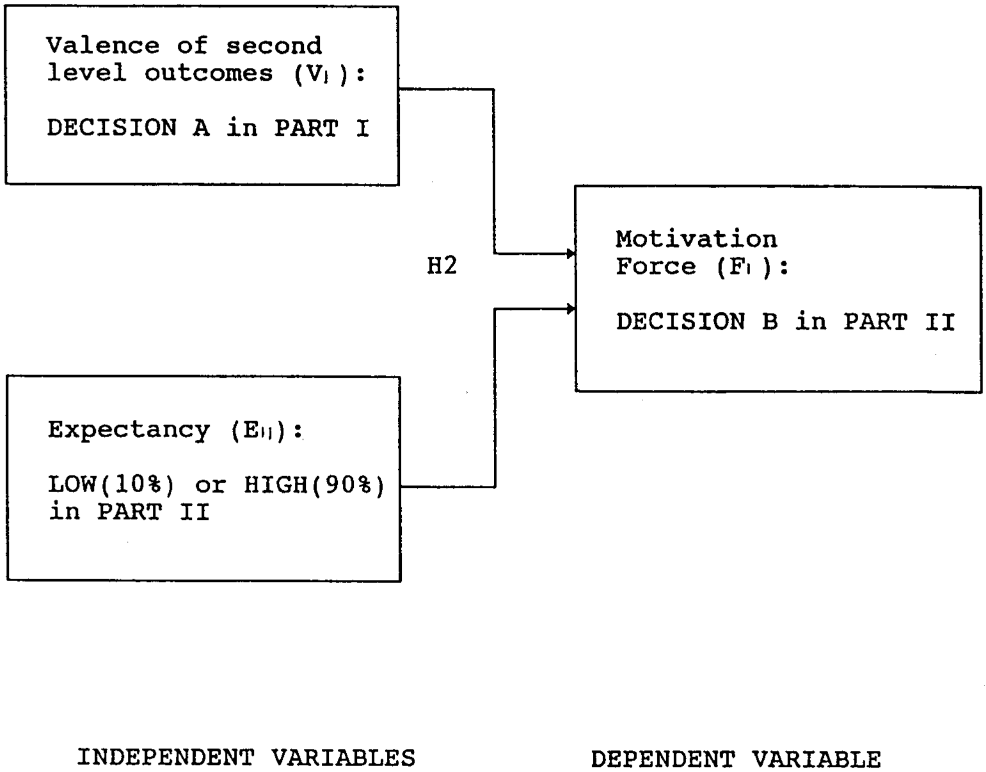


Figure 5. Diagram for the Relationship of Hypothesis 2

The force regression model used to test H2 is :

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

where :

F_i=The motivation(intended effort) level subject is willing to exert to use ES to the bank loan decision context (Decisions in PART II)

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

β_2=standardized the regression coefficient of expectancy

ε =represents random error

Based on the results, at the=0.05 level, all 150 models achieve significance. Therefore at the=0.05 level, data for all of the subjects support the applicability of the force model in the area of bank loan managers' motivation to use ES in the bank loan decisions context, and thus supports hypothesis H2.

Table 7 shows summary information of the regression data analysis, and provides all of the 150 force models' mean R2, mean values, standard deviations and range values. The mean R2 0.8143, supports hypothesis H2.

Table 7. Summary of Within-persons Force Regression Models

	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

β_1 : The perceived attractiveness of the first level outcome of maximum ES use
β_2 : The expectancy (probability) that effort to use the ES to the maximum extent will be successful

3. Results of Analyses Employed to Examine H3

In this part, modeled after Turban's (1993) ninestep development process, ANN models were developed for the valence model. The ANN model is shown in Figure 6.

For the learning algorithm, a backerror propagation algorithm was selected. Therefore, the network structure is a multilayer (two layer) network of continuous perceptrons (i.e., using sigmoid function). The ANNs' learning mode was supervised learning. Furthermore, since there are 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 is feed forward. However, feedback is used to adjust the weights until all training patterns are correctly categorized by the ANNs.

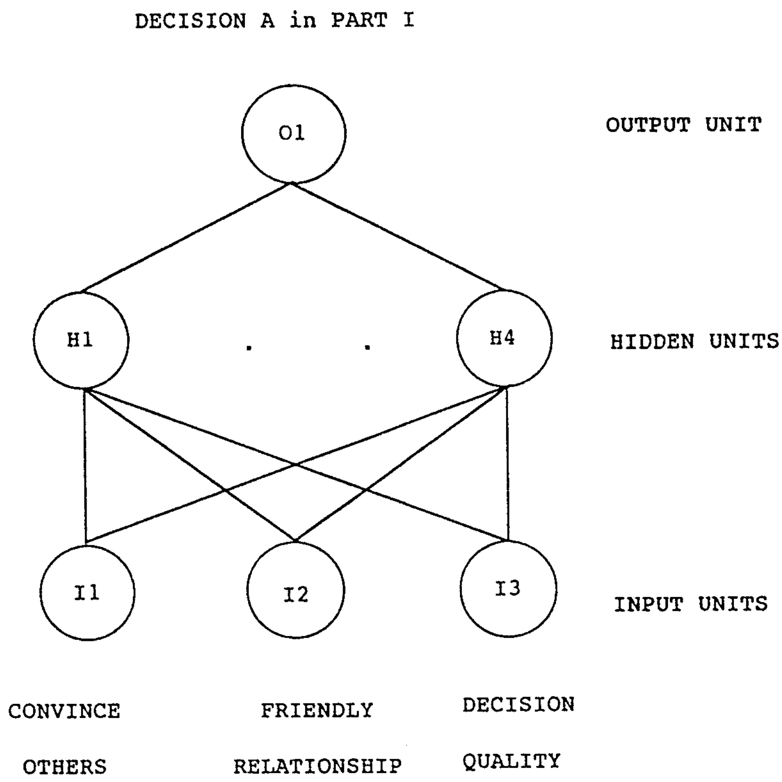


Figure 6. The ANNs for Hypothesis 1

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).

As described in Figure 6, the ANNs model used in this research has three nodes(corresponding to convince others, friendly relationship with customers, and improve decision quality) in input-layer, 4 nodes in hidden-layer, and one node in output-layer. Because input-layer is not counted for describing ANNs layers, this ANNs model represents two layer network. The ANNs model can be expressed by the connection weights from the input layer to the hidden layer to the output layer. The major problem related to ANNs model is that the model can not provide R^2 value, nor p—value. Therefore, the only way to test the ANNs model is to compare neural—net prediction or classification success rates with techniques such as multiple regression or discriminant analysis. In this research, for the hypothesis H3, the prediction power of the ANNs valence models were compared with the prediction power of the within—persons multiple regression valence models.

Each subjects should answer 16 questions in DECISION A. Therefore, total responses of the 150 research subjects were 2,400. Among those responses, 1,200 responses (8 for each subjects) were used to develop ANN and multiple regression models. The other 1,200 responses were used to test the models. Table 8 shows the prediction power of the multiple regression models and the ANNs models for business students.

Table 8. Summary of Multiple Regression vs. ANNs For The Within—persons Valence Model

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 $\alpha = 0.01$

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, 674 out of 1,200 (56.2%) predicted responses generated from the multiple regression exactly matched the real observation responses. In contrast, 1,143 out of 1,200 (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 $\alpha = 0.01$, $v_1 = 149$ 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 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.

4. Results of Analyses Employed to Examine H4

This section describes the testing process for the H4.

The test process for hypothesis 4 was similar to the test process for hypothesis 3. The prediction power of the ANNs models was compared with the prediction power of the multiple regression models. The force ANNs model used in this research have two nodes (corresponding to valence and expectancy) in input-layer, 4 nodes in hidden-layer, and one node in output-layer. The ANN model is shown in Figure 7.

Here each of the 150 subject evaluated 16 choices with hypothetical ESs resulting in 2,400 responses. Again, 1,200 responses (8 for each subjects) were used to develop ANN and multiple regression models, and the other 1,200 responses were used to test the models.

Table 9 provides summary information for the responses.

In total, 552 out of 1,200 (46.0%) of the predicted responses generated from the multiple regression exactly matched the real observation responses. In contrast, 893 out of 1,200 (74.4%) predicted responses generated from the ANN models exactly matched the real observation responses. The total SSE for multiple regression was 8.047, and the total SSE for ANNs was 3.729. Therefore, the F test statistic value was 2.158. The critical F value with $\alpha = 0.01$ 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.

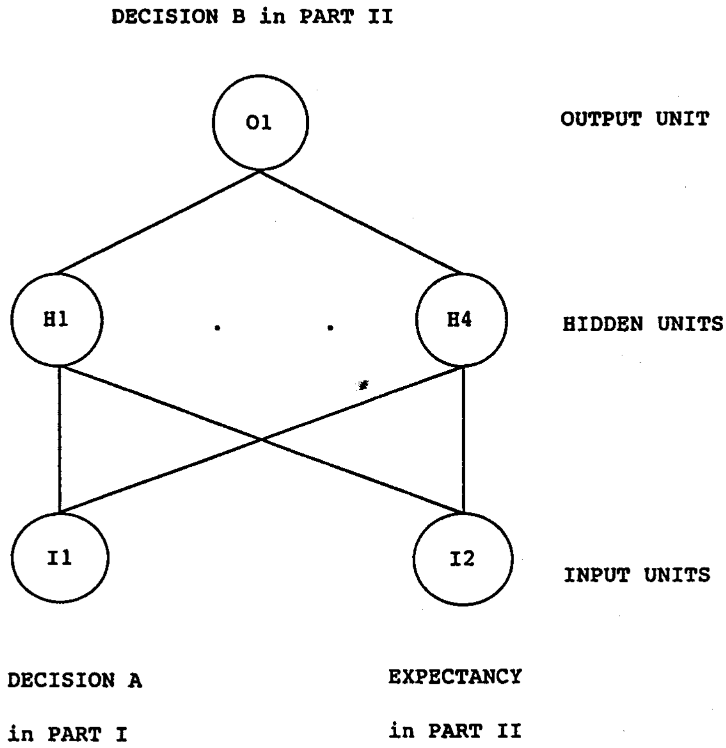


Figure 7. The ANNs for Hypothesis 2

Table 9. Summary of Multiple Regression vs. ANNs For The Within-persons Force Model

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

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

Conclusion

Significant difference at $\alpha = 0.01$

Ⅵ. CONCLUSIONS

Behavioral—related elements are seen as the primary cause of the resistance of end users toward implementation of an ES (Lovata, 1987 ; Turner, 1982). Further, the end—users' acceptance of ES is often regarded as the most important factor for the successful ES implementation. Because the successful applicability of expectancy theory in the bank loan decision context provides a theoretical framework for better understanding of bank loan officers' ES implementation decision processes and provides a more reliable prediction of user response to the acceptance and use of a new ES, the results of this research may provide the developers of ES information to help improve their chances of developing more successful ES without long and expensive trial and error processes that have been used in the past.

In this research, the withinpersons methodology was used, and the result shows that expectancy theory can be used to predict the research subjects' valence or motivation levels of using ES in the bank loan decision context. The results of this research verify that expectancy theory can be successfully applied to explain bank loan managers' motivation to use an ES in the bank loan decision context.

ANNs are a promising method of predicting intended usage of a new ES in terms of predictive accuracy, adaptability, and robustness. Especially, this study provides an early approach to examine human behavior and qualitative decision making with artificial neural networks. The results of this research verify that ANN models have prediction power that is superior to that of multiple regression models to estimate bank loan officers' motivation to use an ES in a bank loan decision context. The confirmation of the ANNs model's superiority in predicting the accuracy of bank loan managers' responses to ES relative to the traditional multivariate techniques can provide ES developers a more powerful measurement tool.

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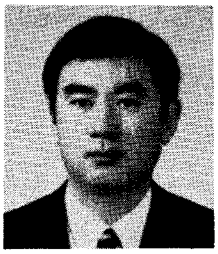

저자 **이용진**은 현재 부산외국어대학교 상경대학 경영정보학과의 조교수로 재직중이다. 고려대를 졸업(1979)하고, 오레곤 주립 대학에서 석사(1987), 미시시피주립대학에서 경영정보학 전공으로 박사학위를 취득(1993)하였다. 주요관심분야는 전문가 시스템, 인공신경망 조직, 객체지향 데이터베이스 등이다.