The Design of EDI Controls using Neural Network

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인공신경망을 이용한 EDI 통제방안 설계

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Abstract

Many organizational contexts should be considered in designing EDI controls to make control systems effective and efficient. This paper gives a description of the neural network model for suggesting the extent of effective EDI controls for a company that has specific organizational environment. Feedforward backpropagation neural network models are designed to predict the state of 12 modes of EDI controls from the state of environment. The predictive power of the system is compared with that of multivariate regression analysis to evaluate the effectiveness of using neural network model in predicting the level of EDI controls. The results show that the neural network model outperforms regression analysis in predictive accuracy. The controls that have high estimated value in the model are likely to be critical controls and EDI auditor or management can enhance investment of IS resources to enhance these controls.

요 약

EDI통제를 설계할 때에는 통제의 효과성 및 효율성을 위해서 조직 및 상황특성을 고려하여야 한다. 본 논문은 특정 환경적 특성을 가지는 조직에 대해 EDI통제 수준을 제안하는 인공신경망 모형을 제안한다. 환경적 특성으로부터 12가지 종류의 EDI통제에 대한 수준을 각각 제안하도록 12개의 역전파 인공신경망 모형이 설계되었다. 본 논문에서 제시한 모형의 효과성을 검증하기 위하여 인공신경망의 예측력을 다중회귀분석과 비교되었다. 예측력 비교결과 인공신경망 모형의 예측력이 다중회귀분석보다 우수함이 입증되었다. 인공신경망을 활용하여 과거의 환경 및 통제수준에 관한 데이터를 학습하여 통제설계에 관한 보다 일관되고 체계적인 의사결정을 할 수 있을 것이다. 또한 보다 높은 수준이 요구되는 통제에 대하여 EDI 관리자나 내부감사인들은 그들의 한정된 자원을 투입하여 구현하도록 할 수 있을 것이다.

Key Word: EDI, neural network, EDI controls

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1. Introduction

EDI (Electronic Data Interchange) refers to the interorganizational exchange of business documen- tion in structured, machine-readable format (Emmelhainz, 1990). The benefits from the implementation of EDI include improved customer service, decreased administrative cost, increased sales, and improved control of data and these appear widespread in many of EDI adopters. EDI may not provide the desired benefits unless EDI messages are processed immediately in internal applications and are then communicated with diverse trading partners in order to gain the economy of scale. EDI can only be of full benefit to an organization though wide spread implementation of the technology.

The extent of these advantages, however, depends upon the usage of EDI controls (Lee et al., 1998). For instance, the retention of records on magnetic media could result in the loss or contamination of data unless specific control mechanisms are devised to protect them such as digital signature or message authentication codes (MAC) that confirm whether or not the data are valid and has been authenticated. The EDI system cannot be further integrated and utilized if it produces erroneous information to inner applications, which leads to degradation of system performance. Management should demand the assurance that adequate controls are in place in the terms of compliance before they implement the EDI system.

The tasks of designing control systems, as performed by EDI auditors, are difficult and unstructured. There exists no normative model of EDI controls. Many alternative forms of controls can exist and many environmental factors affect the design of controls. It is hard to establish if-then rules explaining the choice of controls in certain organizational context. The benefits of controls are hard to be measured quantitatively. Many organizational factors, such as volume of transactions, complexity, and the speed of processing affect the effectiveness of controls. A neural network model is designed to act as a decision aid in recommending the most effective controls in certain organizational context.

There exist AI (artificial intelligence) applications to auditing DSS. Garner & Tsui (1985) built a questionnaire generator that assists auditors know the required evidence that auditors should collect when an error or irregularity has been identified using AI techniques that store the knowledge of experts about a problem domain and elicit this domain knowledge when confronted with a specific problem. Bailey et al. (1985) constructed The Internal Control Model (TICOM) system that enables auditors to analyze and evaluate internal control system. The modeling of an internal control system are performed by using: an Internal Control Descriptive Language (ICDL) compiler that assist an auditor capture the characteristics of an control system and produce a model of control system; a query language that help auditor examine whether control objectives have be satisfied. Morris (1994) applied CBR in the SCAN system to evaluate IS controls. The SCAN system analyzes past cases as a way of reminding an auditor of previous control failures. It suggests a pattern of successful controls and auditors can evaluate the appropriateness of these recommendations in view of current situations. Case-based reasoning (CBR) provides several ad-ntages over rule base reasoning such as the ability to extract the most similar information from experience and dynamically update the system by entering new information (Denna et al., 1992).

The neural network model simulates the operation of human brain. An artificial neural network is a computational structure composed of many non-linear computational elements connected by links with variable weights. A neural network models are usually specified by its pattern of connections between neurons, a learning algorithm, activation function (Fausett, 1994). The networks learning algorithm adjusts the network in response to a set of facts (i.e., a set of known input values and the corresponding correct output values) that are presented successively to the network. After neural networks are trained to identify specific patterns and solve certain problems by producing a correct output from a new set of input values which it has not encountered previously. The strength of a neural network comes from its ability to describe nonlinear relationships that are commonly found in real life situations. They are robust to deal with incomplete and noisy data.

Neural networks have long been recommended for prediction tasks or pattern recognition. One of the most common prediction techniques is regression analysis. Common forms of linear regression analysis implicitly assume normality of variables. These assumptions are frequently violated in the samples used in empirical research since many measurements are of nominal or ordinal nature at best (Eisenbeis, 1977). Because of their capability to capture non-linear relationships in data, it is held that neural networks are better than statistical models to describe the complex pattern of relationships among variables. While statistical models like regression analysis use a predefined functional form to fit the data, neural networks are able to adapt itself to changes in the data where the functional form of the underlying model is unknown and the relationships among the variables are non-linear.

Neural networks have been applied to solve many problems such as image recognition, data compression, signal classification, financial prediction, and function approximation (Fanning and Cogger, 1994; Hecht-Nielsen, 1988, 1990; Trippi and Turban, 1993; Werbos, 1988). The promising classification applications using the neural network approach also include: stock market prediction, prediction of credit card fraud, prediction of bankruptcy and financial distress, letter and word recognition, and diagnostic networks for medical diseases.

Neural networks is a problem-solving and reasoning technique that is rapidly appearing as a powerful artificial intelligence (AI) approach capable of solving expertise-driven, complex problems. Neural networks make the direct use of past experiences (cases) to predict the state of controls. They adapt these generated cases to suggest the most plausible solution to the current problem. EDI auditors collect information of organization by questionnaire and interview guides. They recommend the appropriate controls using experience based on a review of past cases.

The purpose of this paper is to a backpropagation neural network model that is developed to design controls of EDI systems. A neural network model is developed to function in a manner that is compatible with the current practice in designing controls. This paper describes the way how the neural network model functions and compares the prediction accuracy of the backpropagation neural network model with regression analysis.

2. Types of EDI Controls

The objective of EDI controls is to ensure that an organization achieves its goals through the implementation of EDI. They are the activities to safeguard assets, maintain data integrity, accomplish organizational goals effectively, and consume resources efficiently (Weber, 1988). EDI controls in this study focus on asset safeguarding, integrity, and confidentiality. When an EDI system is highly utilized, it is always prudent for management to focus on preventive controls rather than after-the-fact exception reporting and corrective procedures, as they might reduce the impact of system mishaps. EDI controls need to assist in timely identification and resolution of critical problems as they occur but also they need to check the compliance of transactions with accepted standards and prevent errors from reaching into other applications. Trading partners need to promptly identify and acknowledge each other of any alteration, omission, and duplication of messages encountered prior to further processing. The syntactic check of messages needs to be automated to check diverse forms of transactions from a number of trading partners.

Various control dimensions can be used to make a framework of EDI control modes (Lee et al., 1998). In this study, internal and external controls can be classified according to two important control dimensions: formality and automation. The descriptions of the measures of EDI controls are suggested in Table 1. Formal controls are established by management and based on written procedures to be formally abided by. Informal controls are initiated by organization members relying on the values, judgments and communications of members. Automated controls indicate the degree of using automated control procedures and methods.

Measures for EDI controls are newly developed, for which various sources (Chan et al., 1993; ISACA, 1990; Jamieson, 1994; Marcella and Chan, 1993) are referred to (Table 1). They are measured on seven-point Likert-type scales. As it is difficult to measure the use of EDI controls in a quantitative manner (e.g., investment cost of security software, labor cost of security staffs), only qualitative measures are used. The items of variable are averaged to produce the measure of the same variable.

Internal formal application controls are measured using the following four items: system change control by authorization (IFAC1), integrity check of the message before processing in the application (IFAC2), transaction log for the possible errors and collapse (IFAC3), appropriate system login procedures using password (IFAC4). Internal formal communication controls are measured using two items: integrity check after generating EDI messages (IFCC1), authentication of trading partners after receiving EDI messages (IFCC1).

The following five items are suggested to measure external formal VAN controls: back up and recovery plan by VAN (EFVC1), retransmission after correcting erratic messages by VAN (EFVC2), dispute reconciliation procedures by VAN (EFVC3), access control on network by VAN (EFVC4), mailbox access control by VAN (EFVC5). The items for external formal partner controls are the same with external formal VAN controls except that the fifth item is not used and items are reworded to represent the controls initiated by trading partners.

Internal informal controls by IS members are measured by the following five items: recognition of possible propagation of errors from one system to another by IS members (IICIS1), recognition of the importance of their responsibility IS members (IICIS2), ability to judge peers errors in their tasks by experience IS members (IICIS3), ability to cope with the errors effectively by experience IS members (IICIS4), interaction with seniors or peers to cope with problems in their tasks IS members (IICIS5). Internal informal controls by users use these items also but they are reworded appropriately to measure informal controls initiated by users.

Five items are used to measure external informal VAN controls: recognition of the effect of errors in VAN (EICV1), recognition of importance of interorganizational cooperation with VAN (EICV2), processing nonroutine problems between VAN by experience (EICV3), recognition of importance of items in the agreement between VAN (EICV4), interaction between VAN to process message errors (EICV5). The same items are used for external Informal partner controls but they are reworded accordingly to represent the informal controls in relation with trading partners.

Internal automated application controls are assessed using two items, programmed integrity check before processing in application systems (IAAC1) and applying access control software on critical application and files (IAAC2), while internal automated communication controls are measured by automated data integrity check before transmission of EDI messages (IACC1) and automated authentication of trading partners using message code (IACC2).

External automated controls by VAN are assessed using five items: automated transaction log for EDI messages by VAN (EACV1), error message tracing and error reporting by VAN (EACV2), digital signatures (message authentication code) provided by VAN (EACV3), provision of various protocol function by VAN (EACV4), provision of various EDI document standard by VAN (EACV5). The items for external automated controls by partners are the same with external automated controls by trading partners except that the fourth and fifth item are not used and items are reworded to represent the controls initiated by trading partners.

3. Factors affecting EDI Controls

Many organizational contexts should be considered in designing EDI controls to make control systems effective and efficient. EDI controls exist to accomplish organizational objectives under environmental conditions. For example, a large organization with a sophisticated information system should place more emphasis on EDI control systems in comparison to other organizations with weak IS infrastructure. The former should establish more formal controls to manage the large volume of data and technical resources than the latter.

There exists a direct relationship between environments and EDI controls. When environmental information is known, the probable state of EDI controls can be predicted. Thus, when environmental information is known, the probable level of EDI controls can be predicted. It is not feasible for EDI managers to implement every potential control since they require resources. The appropriate levels of various controls should be determined according to organizational contingencies. Different organizational environments require distinct modes and levels of controls. EDI managers and auditors should decide first what sorts of EDI controls are necessary in their organizational context. The guideline can be suggested to select modes of EDI controls in certain organizational context based on a dearth of research on the typology of IS controls and theories of organizational controls. This study adopts the relationship between environments and the mode of appropriate EDI controls in order to define the input and output variables to compose a neural network model.

The industrial and organizational variables are as follows:

1) industrial variables
   external pressure from the industry (E1)
   technological changes (E2)

2) organizational variables
   size (E3)
   professionalism (E4)
   decentralization (E5)
   IS sophistication (E6)
   future role of IS (E7)
   communication openness (E8)

3) task characteristics
   task routineness (E9)

4) partner attributes
   partner trust (E10)
   partner commitment (E11)

The relationships between environmental variables and EDI controls can be deduced from organizational control and EDI literature. For instance, decentralization of organization is related to informal controls, as the implementation of innovation is facilitated by organic structures normally associated with decentralization which facilitates the initiation and testing of new ideas (Russel and Russel, 1992). When EDI professionals have more authority, they are more likely to act on their own judgment and explore novel approaches. When exceptional incidents occur, EDI professionals communicate with others to draw on the latters knowledge and skills. Informal controls are needed to facilitate the communication of ideas in such decentralized organizations.

Task rountiness, for example, is related to the use of internal formal and automated controls. Routine tasks are amenable to standard operating procedures, formal rules and clear performance standards. Managers stress efficiency where activities can be measured quantitatively and are well-defined (Daft and Steers, 1986); this leads to the formalization of work processes. For example, in production departments and assembly lines where such routine processes are typical, the process linking these departments are usually formalized

The efficiency of processing can be improved by automating such easily measured and quantitative routine tasks (Daft and Steers, 1986; Hickson et al., 1969). The speed of repetitive transactions and the lack of human intervention in EDI systems demand prompt detection and correction of errors. Integrated test modules and automated edit checks need to be embedded in internal applications to prevent errors from spreading into other systems. Hence, automated controls are appropriate to cope with routine tasks.

The measures for these factors, i.e., industrial, organizational, task characteristics and partnership attributes are summarized are adapted from measured in the related literature. Industry, organizational attributes, task characteristics, and partnership attributes were measured using measures from the literature. A multiple 7-point Likert-type scale represented each variable except size, two items of IS sophistication.

External pressure is measured by two items, influence of trading partners over EDI implementation (PRES1), and influence of government over EDI implementation (PRES2). Technological change by a 7-point Likert-type scale, perceived degree of change and advance in technology (CHG1). Size was measured by the total number of employees and annual sales. Professionalism is assessed by the proportion of professional staff members with educational backgrounds (PROF1). Decentralization is measured using three items: the degree to which participation of subordinates in company decision making is encouraged (DEC1), the degree to which employees can make their own decisions (DEC2), the extent of concentration of decision making authority (DEC3). IS sophistication is measured by six items: planning and control by steering committee (SOP1), user involvement in the development of IS (SOP2), number of EDP staffs (SOP3), IS budget (SOP4), percentage of administrative applications (SOP5), the percentage of the budget in management controls and strategic planning (SOP6). The following four items are used to assess future role of IS: development of systems for cost reductions and productivity improvement (ROL1), development of systems to provide new ways to compete (ROL2), studying the impact of new IS technologies and areas of application (ROL3), development of IS applications that are vital for long-term strategic objectives (ROL4).

Task routiness is assessed by perception of routineness in performing the five task that respondents selected (TRUT1). Partner trust is assessed by three items: degree of mutual trust between trading partners (TRS1), trust in the benefit of trading partners decision (TRS2), expectation of fair deal from partner (TRS3) Partner commitment is assessed by the extent of efforts to continue the relation by both parties (COMT1).

4. Backpropagation Neural Network Model

Neural networks can assist EDI auditors in searching critical controls through the systematic analysis of the similar cases which have implemented EDI and its controls successfully. The appropriate EDI controls can be predicted using past cases where controls are established effectively. EDI auditors should invest much IS resources to implement the controls that are important in the past cases.

The benefits of neural networks can be suggested as the followings. First, neural network overcome the limitation of human cognitive process of retrieving experiences and professional knowledge which are critical to the quality of the design of EDI controls. The analogical reasoning process of EDI auditors is inevitably constrained by human cognitive limitations and biases. They tend to search for information that supports their own ideas and consistent with their established beliefs. They have difficulty in integrating large quantities of information simultaneously. Neural networks can overcome many of the drawbacks inherent in human reasoning (e.g., inaccuracy, inconsistency, incompleteness) for searching, interpreting, and integrating relevant experiences. EDI auditors review past cases, and suggest necessary controls. But the results of recommendation may have biases according to their limited individual memory and experience. The retrieval of information can be subject to the limited individual memory. Hence they can learn from others experiences by sharing information and knowledge to solve current problems using neural networks.

A three layer architecture consisting of input, hidden, and output layers is used for the prediction of EDI controls. There are five nodes in input and hidden layer, while output layer has one node. Input nodes are composed of the variables that are considered as affecting critically certain mode of EDI controls constitute. Sigmoid function is adopted as activation function: it produces an output value from the activation value. The level of excitation is decided from the activation function after the sum of weighted inputs are compared with the threshold value.

The neural network model in this study adopts backpropagation algorithm to adjust the weight associated with the connection between nodes. The back propagation algorithm uses an iterative gradient descent method to minimize the mean square error between the actual output of a multilayer feedforward net and the desired output. These weights are adjusted and optimized over time to improve performance based on current results. Twelve different models are built to predict twelve modes of EDI controls.

Input variables are determined for each neural network model through correlation analysis. Five environmental variables (that are more related to EDI controls than the other variables) are identified for each model. Table 1 indicates the correspondence of selected input variables for each of the output variables.

[Table 1] Selection of input variables

EDI Controls / Input variables	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12
external influences	v	v	v	v	v		v	v			v	v
technological change			v		v	v	v	v	v	v	v	
size									v			
professionalism	v											
decentralization			v	v		v						v
IS sophistication					v	v	v			v	v	v
future role of IS					v					v		
communication openness	v	v	v	v		v			v	v	v	v
task routineness	v	v	v	v	v		v	v				
partner trust		v		v	v		v	v	v	v	v	v
partner commitment	v	v						v	v			

E1: internal formal application controls
E2: internal formal communication controls
E3: external formal VAN controls
E4: external formal partner controls
E5: internal informal controls by IS department
E6: internal informal controls by users
E7: external informal controls by VAN
E8: external informal controls by trading partners
E9: internal automate d application controls
E10: internal automated communication controls
E11: external automated VAN controls
E12: external automated partner controls

In order to investigate the effectiveness of the neural network model, the neural network model and multivariate regression analysis (that is a commonly used procedure for predicting a continuous dependent variable) are compared in the point of the predictive accuracy for EDI controls. 60 neural network models (five pairs of training and validation sample -please see below) should be trained to provide prediction on 12 dependent variables of controls. These predictions are compared with the true values of the validation sample to compute square root of mean square errors (SMSE). Multivariate regression equations are constructed for 12 control variables. 60 regression equations are also built from the 12 dependent control variables and 5 training sets.

A training sample and a validation sample should be made to proceed the learning and prediction tasks using neural network models or regression models. The weights or parameters of neural network models or regression equations are estimated using training sample. Training sample is composed of 80 (or 90) cases, while validation sample is made up of 20 (or 30) cases. The selection of the cases for training or validation sample is based on the following procedures: (1) The total 110 cases are randomly split into 5 subsets each of which has 20 cases except the last one that has 30 cases; (2) 5 pairs of training and validation samples that have 90 (or 80) and 20 (or 30) cases

〔Table 2〕 Descriptive statistics for variables

Variables	Descriptive Statistics for each variables			
	Mean	Standard Deviation	Maximum	Minimum
external influences	4.09	1.24	1.00	7.00
technological change	4.10	1.24	2.00	7.00
size	0.01	0.89	-0.53	4.50
professionalism	4.08	1.40	1.00	7.00
decentralization	3.22	0.99	1.00	5.33
IS sophistication	-0.13	0.47	-1.22	1.48
future role of IS	5.44	0.94	2.50	6.50
communication openness	4.13	1.43	1.00	7.00
task routineness	5.50	0.81	3.50	7.00
partner trust	5.22	1.09	1.00	7.00
partner commitment	4.85	0.90	2.33	7.00
internal formal application controls	2.34	0.89	1.0	4.20
internal formal communication controls	4.07	1.39	1.00	7.00
external formal VAN controls	4.25	1.44	1.00	7.00
external formal partner controls	4.26	1.34	1.00	6.60
internal informal controls by IS members	4.38	1.30	1.20	7.00
internal informal controls by users	4.76	1.14	1.00	7.00
external informal controls for VAN	4.87	1.69	1.00	7.00
external informal controls for partners	4.91	1.20	1.00	7.00
internal automated application controls	4.91	1.18	1.20	7.00
internal automated communication controls	4.92	1.53	1.00	7.00
external automated controls by VAN	5.09	1.19	1.25	7.00
external automated controls by trading partners	5.26	1.47	1.50	7.00

respectively are composed (the validation samples are indicated as A, B, C, D, E in Table 3 and 4); (3) Each of subsets is used as validation sample one by one, while the cases left over are used as training sample.

The SMSEs in the neural network and regression model across 5 validation samples and across 12 target control variables are given in Table 3 and 4. Average SMSEs of regression model are higher than those of the neural network model across 5 holdout samples for 9 out of 12 controls. This is also the case for the 6 classes of controls. Average SMSEs for six classes of controls are given in Table 5. The neural network model outperforms the regression model in predictive ability for all of six classes of EDI controls (Table 5).

[Table 3] Square root of mean square error (SMSE) of the neural network model
(*: SMSE is slightly higher in the neural network model)

Controls \ Validation Sample	A	B	C	D	E	Average
Internal formal application controls	1.237	0.905	0.783	0.807	0.956	0.938
Internal formal communication controls	1.850	0.879	1.144	1.424	1.381	1.336
External formal VAN controls	1.855	1.092	1.327	1.926	1.184	1.477
External formal partner controls	1.279	1.494	0.935	1.274	1.278	1.252
internal informal controls by IS members	1.109	0.759	1.040	0.957	1.273	1.028
internal informal controls by users	1.224	1.234	1.208	1.540	0.851	1.211*
external informal controls for VAN	1.363	0.983	0.930	1.858	0.817	1.190*
external informal controls for partners	0.898	1.036	1.317	0.979	0.984	1.043
internal automated application controls	1.388	1.548	1.286	1.830	1.601	1.531
internal automated communication controls	1.335	1.244	1.278	1.395	1.731	1.397*
external automated controls by VAN	2.713	1.845	1.216	1.863	1.340	1.795
external automated controls by trading partners	0.703	0.732	0.700	0.716	0.967	0.764

[Table 4] Square root of mean square error (SMSE) of regression model

Controls \ Validation Sample	A	B	C	D	E	Average
internal formal application controls	1.237	2.616	0.832	0.918	0.919	1.304
internal formal communication controls	5.048	0.902	1.118	1.432	1.268	1.954
external formal VAN controls	2.296	1.017	1.274	1.938	1.151	1.535
external formal partner controls	1.856	1.455	0.926	1.123	1.170	1.306
internal informal controls by IS members	1.443	0.936	1.030	0.937	1.109	1.091
internal informal controls by users	1.194	1.245	1.164	1.481	0.832	1.183
external informal controls for VAN	1.094	0.951	1.039	2.008	0.814	1.181
external informal controls for partners	0.979	1.026	1.390	0.976	1.006	1.075
internal automated application controls	1.648	1.659	1.354	3.994	1.463	2.024
internal automated communication controls	1.429	1.229	1.293	1.165	1.775	1.378
external automated controls by VAN	2.659	2.541	1.284	1.851	0.847	1.836
external automated controls by trading partners	0.745	1.032	0.713	1.006	0.947	0.888

[Table 5] Average of square root of mean square error

Control Class	BPN	Regression
internal formal controls	1.137	1.629
external formal controls	1.364	1.421
internal informal controls	1.120	1.137
external informal controls	1.117	1.128
internal automated controls	1.464	1.701
external automated controls	1.279	1.362

[Table 6] Paired t-test of square root of mean square error
(*: p < 0.1, **: p < 0.05, ***: p < 0.01)

Control Class	BPN	Regression	No. of pairs	t-value	p-value
formal controls	1.251	1.525	20	-1.53	0.072*
Informal controls	1.118	1.133	20	-0.53	0.302
Automated controls	1.372	1.532	20	-1.36	0.094*
Total set	1.247	1.396	60	-2.07	0.022**

The significance of the difference in the average SMSEs across class of controls (i.e., formal controls, informal controls, and automated controls) can be examined using paired t-test (Table 6). The SMSEs of neural network model are significantly lower than the regression model for the control class of formal and automated controls, and for total set..

5. Conclusion

The analogical reasoning process of EDI auditors is inevitably subject to human cognitive limitations and bias. And their memories are variable and finite. And they are limited in their information-processing capacity. They cannot be completely consistent in searching for relevant experiences, interpreting them, and applying them to problem solving.

A backpropagation neural network model is developed to reduce cognitive burden of EDI auditors in identifying analogous cases to figure out which controls fit a firm with certain environmental context. The effectiveness of this system is assessed by comparing its accuracy in predicting the state of controls with that of multivariate regression analysis. The neural network system significantly outperforms multivariate regression analysis in the average predictive power.

The neural network model is designed to aid the EDI auditors in suggesting the extent of effective controls for a company that has specific organizational environment and will enhance the utilization of data available in the forecasting process. The controls that have high estimated value in the model are likely to be critical controls and EDI auditor or management can enhance investment of IS resources to enhance these controls. EDI auditors can obtain an idea about the desirable state of controls by reviewing the prediction results.

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