Supplier evaluation model for computer auditing and decision-making analysis

Kuang-Hsun Shih
Department of Banking and Finance, Chinese Culture University, Taipei, Taiwan

Hsu-Feng Hung
Department of Business Administration, National ChengChi University, Taipei, Taiwan, and

Binshan Lin
College of Business Administration, Louisiana State University in Shreveport, Shreveport, Louisiana, USA

Abstract

Purpose – The purpose of this paper is to present a model and a supporting approach for effective supplier selection decisions.

Design/methodology/approach – Structural equation modeling (SEM) and confirmatory factor analysis are applied to test the evaluation principles and samples. Next, the data tested by SEM is used for artificial neural network (ANN) by Likert and fuzzy scales to structure a classification model, accompanying with canonical discriminate analysis (CANDISC) to diminish variables. After the training and test of the model, multiple discriminate analysis is applied to compare the accuracy of the classification. Last, the CANDISC variable reduction method with ANN classification model utilized in the study is applied.

Findings – The supplier selection model designed with ANN classification model and fuzzy scales will be more effective than with the traditional statistics analysis.

Research limitations/implications – The new paradigm for decision making includes a combination of several effective methods and analysis.

Practical implications – This research provides an integrated model for internal auditors and managers to classify their supplier selection decisions.

Originality/value – This paper contributes to the new approach of the decision model building process for computer auditing and improves the classification accuracy effectively.

Keywords Computers, Auditing, Internal control, Supplier evaluation, Cybernetics

Paper type Research paper

1. Introduction

Growing competition in globalized markets is steadily narrowing gaps in the quality and performance of different goods. Sarmah *et al.* (2006) suggests this phenomenon has drawn the attention of both researchers and industry players, and prompted them to rethink the question of how to manage enterprise operations effectively and efficiently. Supply chain can be defined as an organized network that makes use of different processes and activities to transmit the value of goods and services to the end consumer, while supply chain management (SCM) is a method of designing, managing,

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and controlling supply chains, with an eye to integrating processes (Joyce, 2006; Ahmed, 2009). The main goal of SCM is to create value by improving customer service and lowering prices (Koskinen, 2009).

SCM tools include the intelligent supplier management tool (Choy *et al.*, 2005; Humphreys *et al.*, 2002), internal and external supply chain integration (Tessarolo, 2007), management of supplier relationships (Wu and Shen, 2006), and supplier selection (Choi and Chang, 2006). All of these can be used, together with advanced, modern information technologies or analytical methods, to carry out management, and it would even be possible to use information systems to integrate supplier management, supplier selection, and purchasing strategies (Lee *et al.*, 2001), thereby making an enterprise's management more effective and competitive.

From an auditor's perspective, one of the key issues in efforts to build a supply chain within the purchasing and payments cycle is the process of supplier selection, but the factors affecting supplier selection are many, and supplier selection is a complex, multifaceted process. An enterprise's senior management is usually unable to be directly involved in the decisions, so they must establish systematized models and use effective decision-making tools if they are to help the decision makers make good selections. Previous studies on supplier selection (Jayaraman *et al.*, 1999; Handfield *et al.*, 2002; Kauffman and Popkowski Leszczyc, 2005; Andrabi *et al.*, 2006) have employed many different quantitative decision-making methods to help ensure an objective and effective supplier selection process, and treat the final judgment resulting from this process as reference in the actual making of a decision.

The objective of this paper is to present a model and a supporting approach for effective supplier selection decisions. The remainder of the paper is organized into five sections. Section 2 reviews previous work on supplier selection and artificial neural networks (ANNs). Section 3 lays out research methods, processes, and data sources. Section 4 develops detailed descriptions and discusses the empirical results. Finally, conclusions are presented in Section 5 with managerial and theoretical implications.

2. Literature review

SCM seeks to integrate internal operating activities and decision-making processes with those of outside partners to achieve the goal of improved competitiveness (Li and Wang, 2007). Purchasing is one of the factors that most affects the performance of SCM, while supplier selection also has a direct impact upon the purchasing decision aspect of SCM (Wu and Shen, 2006; Wei *et al.*, 2009). In addition, supplier selection has an important impact upon the inventory management and delivery performance aspects of SCM (Basnet and Leung, 2005; Kawtummachai and Hop, 2005). Both quality and delivery performance have the dominant impact upon SCM (Basnet *et al.*, 2003).

There are many different supplier selection methods, and most employ traditional statistical methods and quantitative models. However, a few employ ANNs for classification modeling, and none of the literature in this field has yet shown in combination with structural equation modeling (SEM). SEM can be used to rigorously test the fitness between sample data and structural modeling. Moreover, neural networks have worked extremely well in many different fields. For these reasons, the present study makes use of SEM, ANNs, and multiple discriminate analysis (MDA) to establish a method for basic analysis of supplier selection models.

2.1 Supplier evaluation criteria

Supplier differentiation can be defined as the identification of differences between some of the characteristics of different suppliers, such as organizational culture, production processes, technical capability, and geographic distribution (Choi and Krause, 2006). Despite all the perceived benefits of forging integrated business relationships, there are still some derived risks about entering into these relationships (Iacovou *et al.*, 1995). These risks include specific-capital transaction, asymmetries information, and loss of resource control (Sutton *et al.*, 2008). Auditors may focus more on the supplier evaluation criteria to select appropriate suppliers for improving organizational competitiveness.

Supply chain performance can be viewed as sustained effective activity over past, present, and future periods (Sari, 2008; Sevkli *et al.*, 2008; Koskinen and Hilmola, 2008). The question of what would constitute an effective and efficient supply chain performance evaluation method is becoming an increasingly important topic in supply chain discussions (Catt *et al.*, 2008; Chang *et al.*, 2007; Gulledge and Chavusholu, 2008). Accordingly, the present study examines 14 previous studies and summarizes evaluation criteria. The criteria that we found are shown in Table I.

As Table I shows, purchasers and firms most often put top stress on the following three factors in selecting suppliers:

(1) quality;

(2) price; and

(3) delivery performance.

Author (year)	Evaluation criteria
Dickson (1966)	Quality; price; delivery; performance history; warranties and claims policies; production facilities and capacity; technical capability; financial position; procedural compliance; communication system; position and reputation; desire for business; management and organization; operating controls; repair service; attitude; impression; packaging capability; labor relations record; geographical location; amount of past business; training aids; and reciprocal arrangements
Cusumano and Takeishi (1991)	Financial matters; price; quality; delivery; technical capability; and past business relationship
Weber and Current (1993)	Price; delivery dependability; and product quality
Chaudhry *et al.* (1993)	Quality; delivery capability; and price breaks
Swift (1995)	Products; usability; dependability; experience; and price
Choi and Hartley (1996)	Financial matters; consistency; relationship; flexibility; technical capability; service; reliability; and price
Jayaraman *et al.* (1999)	Quality; nature of products; lead time; and warehousing capability
Lee *et al.* (2001)	Costs; quality; delivery; and service
Muralidharan *et al.* (2001)	Quality; technical capability; and delivery
Muralidharan *et al.* (2002)	Quality policy; delivery time; price; professional and technical expertise; financial condition; past performance; equipment; flexibility; and service
Prahinski and Benton (2004)	Quality; delivery performance; price; ability to respond to changed needs; and support services
Kreng and Wang (2005)	Costs; quality; delivery reliability; lead time; and timeliness of delivery
Pi and Low (2005)	Quality; timeliness of delivery; price; and service
Chang *et al.* (2007)	R&D capability; costs; quality; service; and responsivity

Table I. Supplier selection criteria employed in 14 previous studies

Researchers also suggest service and flexibility as important supplier selection criteria (Choi and Hartley, 1996; Lee *et al.*, 2001; Muralidharan *et al.*, 2002; Pi and Low, 2005; Prahinski and Benton, 2004; Chang *et al.*, 2007). Accordingly, the present study defines the five criteria as follows:

(1) *Quality.* The quality of goods provided by the supplier.

(2) *Price.* The amount paid by the enterprise to buy goods from its suppliers.

(3) *Delivery performance.* How well a supplier succeeds in delivering goods according to schedule?

(4) *Service.* The after-sales service and support provided by a supplier.

(5) *Flexibility.* The ability of a supplier to accommodate changes in the enterprise's production plans.

2.2 Fuzzy scale

Chen and Hwang (1992) use fuzzy arithmetic to convert linguistic terms into crisp numbers, and put forward eight conversion scales for the reference of decision makers. The conversion is accomplished by first providing a maximizing set and a minimizing set:

$$\mu_{\max}(X) = \begin{cases} x, & 0 \leq x \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

$$\mu_{\min}(X) = \begin{cases} 1 - x, & 0 \leq x \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.2}$$

If we assume that M is a fuzzy variable, then the left score for M is $\mu_L(M)$ while the right score for M is $\mu_R(M)$, the values of which can be obtained by the following equations:

$$\mu_L(\mathrm{M}) = \sup[\mu_M(\mathrm{X}) \wedge \mu_{\min}(\mathrm{X})] \tag{2.3}$$

$$\mu_R(\mathrm{M}) = \sup[\mu_M(\mathrm{X}) \wedge \mu_{\max}(\mathrm{X})] \tag{2.4}$$

In these equations, $\mu_L(M)$ and $\mu_R(M)$ are both the only positive whole crisp numbers within the [0, 1] range. By solving for the left and right scores for M, we can obtain the total score for M as follows:

$$\mu_T(\mathrm{M}) = \frac{[\mu_R(\mathrm{M}) + 1 - \mu_L(\mathrm{M})]}{2} \tag{2.5}$$

μ_T is the fuzzy number after conversion. If we use a post-conversion five-grade scale, the corresponding fuzzy memberships would be 0.091, 0.283, 0.5, 0.717, and 0.909, respectively.

2.3 Supplier classification methods and evaluation models

Weber *et al.* (1991) classified three main methods for quantification of supplier selections – linear weighted models, quantitative approaches, and statistical probability methods. Linear weighted models were used the most, while statistical probability models were used the least.

Researchers have used statistical probability theory to establish a selection model. Hinkle *et al.* (1969) was the only one among the earlier studies to use cluster analysis to evaluate supplier classifications, while Soukup (1987) used probability theory to modify the linear weighted method in order to improve the measurement of criteria weightings. More than one type of statistical probability model has been used for supplier classification. The present study uses MDA and ANNs to examine the accuracy of these two research tools.

2.3.1 MDA and canonical discriminant functions. MDA is used for statistical analysis of classification response variables versus analytical explanatory variables. Where the subject groups to which all data objects belong are already known, MDA is used to obtain the function that will most correctly identify the classification of these data objects.

Discriminant functions can be used to analyze for different sample data. When each group of data is normal and the covariance matrices are identical, the linear discriminant function rule can be used. When each group of data is normal but the covariance matrices are not identical, then a posteriori discriminate analysis can be used. And when the individual data groups are not normal, then Fisher's linear discriminant function analysis, so-called canonical discriminant analysis (CANDISC), can be used.

CANDISC is a statistical method involving use of the Fisher method and appropriate canonical analysis principles to establish canonical discriminant functions. The significance of each explanatory variable can be known from its discriminant power, while the impact of the explanatory variables upon forecasts and classifications depends on the canonical discriminant coefficients.

Our study uses the holdout method, whereby the data objects of all samples are classified under one of two categories; one is construction data, while the other is validation data, the latter of which are used to evaluate the constructed data. These data are used to establish a model function to test the accuracy of validation data classifications. The results show whether the construction data can be used effectively enough to meet the anticipated needs, thus enabling a determination regarding whether the model can be used.

2.3.2 Artificial neural networks. ANN models can be categorized into four types:

(1) supervised learning networks;
(2) unsupervised learning networks;
(3) associate learning networks; and
(4) optimization application networks.

With supervised learning networks, training examples with complete input and output variable values are obtained from problem spaces, and in the process the network learns the internal correspondence rules between the input variables and output variables. These rules are then used to infer output values in new cases where only input values are available.

Supervised learning networks can be applied to such things as classifications and forecasts, and represent the most important and successful application of ANNs to date. They have been applied in many enterprises for such purposes as auto engine diagnosis, process control, analysis of mineral deposit detection signals, and stock price forecasts. Back-propagation networks (BPNs) are currently the most notable and widely applied type of ANN learning model. In basic principle, they use the gradient steepest descent method to minimize the error function. A BPN is a type of supervised learning network, and is therefore appropriate for diagnosis classification, forecasting, etc. The present study uses the excellent forecasting and analytic capabilities of BPN to establish a supplier selection model.

The ANN model of data mining analysis have been discussed and improved in many papers (Andrew, 2005; Fish and Segall, 2004). Such as, Satsangi *et al.* (2003) used the ANN model to discuss the systems dynamics issue. Segall and Zhang (2006) applied the ANN, genetic algorithms, regression, and MDA to discuss the data mining issue. In general, the ANN model could solve the prediction and classification problem and build effective analysis model to help decision makers.

3. Research methods

We employ a questionnaire that includes five supplier evaluation criteria – quality, price, delivery performance, service, and flexibility. Likert five-point scale measurements are used as the basis for giving suppliers scores of 5 – very satisfactory, 4 – satisfactory, 3 – fair, 2 – unsatisfactory, and 1 – very unsatisfactory. Then we assign to each supplier an evaluation grade of A – excellent supplier, B – fair supplier, or C – poor supplier. For each questionnaire the researcher engages in purposive sampling, taking the initiative to contact the respondent, explain the questionnaire, and fill in the responses. A total of 217 supplier evaluations have been collected for the purpose of establishing and analyzing a model. With respect to the respondents' industries and personal identities, we intentionally interview respondents from different backgrounds in order to use generally applicable and diverse viewpoints when examining whether the model established can be effectively applied in any industry.

Research procedure. We start by making on-site visits and talking to supplier evaluators and purchasers. We ask them to fill out the questionnaire and give each supplier a supplier score (from 1 to 5) and an evaluation grade (from A to C). Second, we use SEM to test the data. We examine the fit between the data and the model, and carry out confirmatory factor analysis (CFA), and the results prove that the questionnaire data have good internal consistency, and that our criteria have a high degree of homogeneity. In addition, we convert between the Likert scale and fuzzy scale for the collected questionnaires so that the data types have two different data measurement states, in hopes of using comparative analysis in order to examine which kind of scale provides statistical data that support a more effective classification model. Finally, we use MDA and ANN to establish a supplier classification model which, together with a CANDISC variable reduction model, we use to determine which combination yields the most accurate classification model.

The present study first defines the evaluation point system for the five continuous input variables and the category codes for the categorical output variables. Second, we use SEM modeling to analyze the preliminary fit of the samples, overall fit, and goodness of fit for the internal structure. After that, the study uses proportionate stratified random sampling to segregate sample data into model establishment data (training samples) and model validation data (testing samples), then MDA modeling is used to carry out testing and analysis, then establishes an ANN model. MDA analysis models are classified as either Likert or fuzzy data. These data are plugged into the MDA model, and we observe to see their classification effectiveness. After that, we use CANDISC variable reduction functions, using several CANDISC function replacements to analyze the five input variables and observe whether they can effectively improve classification accuracy. Finally, the combination that affords the most effective MDA model classification is selected as the final MDA model classification accuracy.

When establishing the ANN model, therefore, training accuracy and validation accuracy are the accuracy values that most concern us; testing accuracy values are used as reference to inform judgments regarding model stability, and are not of primary importance with respect to model accuracy. Before analyzing the ANN model, the present study first tests the classification effectiveness of the linear model without using any hidden layers, then one hidden layer is added, the number of neurons is adjusted, and we observe to see whether switching to a non-linear model can improve classification accuracy. If it does not, then application of the ANN model is pointless. After a hidden layer has been added and the number of neurons adjusted, adjustment of the parameters is also an important step affecting the classification accuracy of the ANN model. For this reason, the present study selects the initial values for number of learning cycles, initial learning rate, and the momentum factor, and adjusts the parameters to improve the final accuracy of the model.

We also divide input data for the ANN model into Likert scale data and fuzzy scale data, and use neuron coding to carry out data conversion for output variable categorical data. We then examine to see which data (i.e. the data converted under which scale) yield the ANN model with the most accurate classification, and finally. We use several CANDISC function replacements for the five input variables, and plug them into the ANN model and observe whether they can effectively improve classification accuracy. Finally, from among various ANN model accuracy output variables, we select the best performing model as the final ANN model output.

Accordingly, within the topic of supplier classification, the present study is concerned primarily with using the ANN model together with fuzzy scale data conversion, and then adding a CANDISC variable reduction model, to evaluate whether it can be more effective than the traditional MDA statistical method, and whether it can be developed into a new paradigm for supplier selection decision-making models. Therefore, the analytical steps set out below must all be carried out with statistical rigor to seek maximum effectiveness for the MDA model, and to ensure that the results of this study are objective and unbiased.

4. Empirical analysis

4.1 Confirmatory factor analysis

CFA is mainly applied in two situations. First, during the development of a measurement tool, it is used to evaluate the appropriateness of the measurement tool's factor structure. Second, it is used to examine whether the relationship between latent variables conforms to certain theoretical concepts. This examination is referred to as the testing of theoretical concepts. A review of past literature shows that quality, price, delivery performance, service, and flexibility are the five main criteria for supplier selection, therefore the current study uses LISREL software to run structural equations to perform confirmatory factory analysis and ascertain the relationships between observed variables and latent variables, thereby examining the question of how to assess the fit of the linear structure model, i.e. the degree to which the analytical model for factor assessment can explain actually observed data.

SEM includes the following methods for estimating parameters: instrumental variable, two-stage least squares, unweighted least squares (ULS), maximum likelihood (ML), generalized least squares, elliptical distribution theory, and asymptotic distribution free. Generally speaking, the ML method is usually used for estimation of parameters, but this method requires an assumption that observed variables will exhibit multivariate normal distribution, and that a larger sample is better. In addition, testing of the collected sample data yields peak values of 0.608, 0.383, 0.601, 0.806, and 1.004, which represents normal distribution. But although the assumption of normal distribution is satisfied, the requirements of the ML method are still not met, therefore the present study adopts the ULS method for estimating parameters.

4.1.1 Testing the preliminary model fit. The present study uses these three criteria to test the model's preliminary fit. Table II shows that error variance is greater than zero, and thus meets the first criterion for preliminary fit. Next, the test *t*-statistic shows that error variance meets the level of significance, and thus meets the second criterion for preliminary fit. In addition, standard error for each parameter falls between 0.098 and 0.152, so it is clear that standard error is not excessive and thus meets the third criterion for preliminary fit. To summarize the abovementioned assessment criteria, CFA of data obtained through testing done using the Likert scale, shows that the data meet the preliminary fit criteria, which indicates an acceptable preliminary fit between the model and the observed data. In addition, all factor loadings of the measurement model are significant at 0.05. The estimated values for measurement model parameters are shown in Table III.

4.1.2 Testing the overall model fit. The purpose of testing overall fit is to evaluate the degree of overall fit between the model and the observation data collected during the study. Table IV shows a χ^2-value of 23.92 for the model established in the present study. Next, the model has a NFI of 0.89, CFI of 0.92, IFI of 0.92, GFI of 0.98, and AGFI of 0.95, all of which are near to or greater than 0.9. And third, SRMR is 0.064, thus is below 0.08 and meets the suggested evaluation criteria. On the basis of these indicators, the CFA model used in the present study shows an acceptable fit with the

Table II. Estimation for error variance of observed variables

Aspect	Parameter variable	Parameter estimate	Standard solution	SE	*t*-value
Quality	δ_1	0.90*	0.90	0.10	8.68
Price	δ_2	0.75*	0.95	0.10	7.61
Delivery performance	δ_3	0.87*	0.70	0.12	7.03
Service	δ_4	0.67*	0.51	0.15	4.35
Flexibility	δ_3	0.93*	0.56	0.17	5.58

Notes: *Significance level of 0.05; the *t*-value shows a significant difference observed data, i.e. this theoretical model can be used to interpret observed data. The concept measurement model is shown in Figure 1.

In summary, the assessment criteria presented above show that the CFA model used in the present study has acceptable internal quality, and is appropriate for use in interpreting observed data. The testing model established in the present study is shown in Figure 1. Using the CFA model, we find acceptable values for all assessment criteria. This means that there is an acceptable fit between the model established by the present study for analysis of supplier selection criteria (including quality, price, delivery performance, service, and flexibility) and the observed data, i.e. this testing model is an evaluation construct that contains these five evaluation measurement criteria.

4.2 Using multidiscriminate analysis to establish a model

First, we use proportionate stratified random sampling on 217 items of sample data to extract 197 items of model training data and 20 items of model testing data (approx. 10:1). This is done because of a small number of samples. That is why we decided to use a 10:1 ratio in establishing the model. Information on the training samples and testing samples are shown in Table V.

After that, we use the Likert scale to plug the sample data into the MDA model to carry out testing classification accuracy. Two normality assumptions (with identical

Aspect	Parameter variable	Parameter estimate	Standard solution	SE	*t*-value
Quality	λ_{X1}	0.32*	0.32	0.06	5.83
Price	λ_{X2}	0.19*	0.21	0.05	3.67
Delivery performance	λ_{X3}	0.55*	0.55	0.06	9.56
Service	λ_{X4}	0.80*	0.70	0.08	10.62
Flexibility	λ_{X5}	0.66*	0.66	0.08	10.59

Notes: *Significance level of 0.05; the *t*-value shows a significant difference

Table III. Estimation for measurement model parameters

χ^2	DF	NFI	CFI	IFI	GFI	AGFI	SRMR
23.92	5	0.89	0.92	0.92	0.98	0.95	0.064

Table IV. Testing of overall model fit

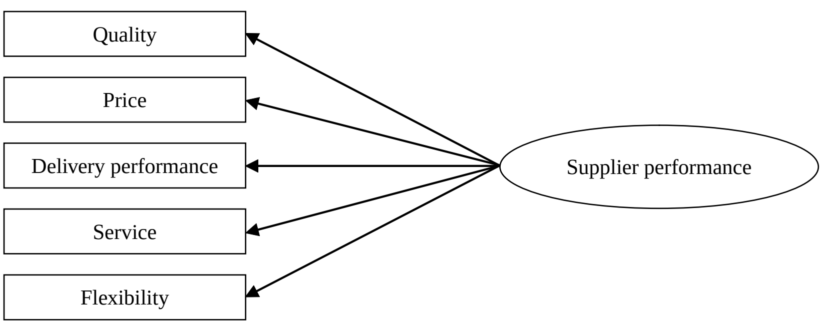

Figure 1. Conceptual measurement model of supplier performance

covariance values and different covariance values) are used to check their differences. The test statistics for the analysis results are shown in Tables VI and VII.

As shown in Tables VI and VII at a reliability level of 0.01 all the input variables reach the level of significance, which means that all the influencing factors tested in the present study using the SEM model have a significant impact upon the MDA model classification results. We, therefore, proceed to plug the five input variables into the classification model and establish an MDA classification model. It can be seen in the relevant test statistics of Table VIII that MDA classification has good significance, which proves that this model should be very effective and reliable as a means of classifying supplier performance.

The next step is CANDISC. Tables VIII-X show the statistics yielded through CANDISC. These statistics are screened to select significant canonical discriminant functions, and canonical scores are plugged into discriminant functions to analyze classifications. We then extract two canonical discriminatory functions to represent the effect of all independent variables upon supplier performance.

Table V. Statistical table of sample data class descriptions

Sample class	Class A	Class B	Class C	Total
Training samples	76	85	36	197
Testing samples	8	9	3	20
Total samples	84	94	39	217

Table VI. Test statistics for MDA variables

Variable	Label	Total SD	R^2	$R^2/(1-R^2)$	F-value	Pr > F
X1	Quality	1.0030	0.2579	0.3475	33.71	< 0.0001
X2	Price	0.8710	0.0538	0.0569	5.52	0.0047
X3	Delivery performance	1.1187	0.2082	0.2630	25.51	< 0.0001
X4	Service	1.1328	0.1695	0.2041	19.80	< 0.0001
X5	Flexibility	1.2749	0.1117	0.1257	12.20	< 0.0001

Table VII. MDA test statistics

Statistic	Value	F-value	Num DF	Den DF	Pr > F
Wilks' lambda	0.54875923	13.30	10	380	< 0.0001
Pillai's trace	0.46393568	11.54	10	382	< 0.0001
Hotelling-Lawley trace	0.79915897	15.13	10	282.26	< 0.0001
Roy's greatest root	0.76907904	29.38	5	191	< 0.0001

Table VIII. Canonical discriminant function coefficients

No. canonical	Canonical correlation	Adjusted canonical correlation	Approximate SE	Squared canonical correlation
1	0.659344	0.649181	0.040376	0.434734
2	0.170885	0.129010	0.069343	0.029202

Canonical discriminant function correlations are shown in Table VIII and can be used to judge their impact upon the classification model. Table IX shows canonical discriminant function eigenvalues and explanatory variances. Table X tests whether canonical discriminant functions are statistically significant. The first canonical discriminant function has good statistical significance and therefore can appropriately be plugged into the MDA model and used as the basis for analyzing work performance classification. Accordingly, forward selection is used to plug canonical discriminatory functions one at a time into the MDA model. Table XI shows the impact of individual independent variables within the canonical functions. The coefficients can be used to evaluate the degree of impact of those variables within the canonical functions upon classification results.

The classification accuracies are shown in Table XII. After the Likert scale is converted into the fuzzy scale using the analytical steps described above, we again carry out the same analytical steps and discover that there is no significant difference in the resulting MDA model test statistics or canonical discriminatory function test statistics. In both cases, there is a high degree of significance. The post-conversion fuzzy scale is plugged into the MDA model, analytical comparisons are performed, and we observe to see whether there is any significant variance between the resulting classification effectiveness and that obtained with the model established using the Likert scale.

Table XII shows that the classification accuracy of the fuzzy scale is slightly better than that of the Likert scale, but the difference is not significant. And using canonical discriminant functions as a tool for screening variables does not effectively raise its classification effectiveness. The reason is that all of the effect variables are significant variables, therefore carrying out variable reduction actually reduces the classification

No. canonical	Eigenvalue	Difference	Proportion	Cumulative
1	0.7691	0.7390	0.9624	0.9624
2	0.0301	–	0.0376	1.0000

Table IX. Canonical discriminant function eigenvalues and explanatory variances

No. canonical	Likelihood ratio	Approximate F-value	Num DF	Den DF	$\Pr > F$
1	0.54875923	13.30	10	380	< 0.0001
2	0.97079845	1.44	4	191	0.2235

Table X. Canonical discriminant function test statistics

Variable	Canonical coefficient 1	Canonical coefficient 2
X1	0.6750590453	0.0439559138
X2	0.3237840613	0.4991686009
X3	0.3611516991	−0.6449027355
X4	0.4242175224	−0.1094601341
X5	0.1009241176	0.7092749976

Table XI. Pooled within-class standardized canonical coefficients

Table XII.
Likert and fuzzy scales MDA classifications

Input variable types	Model with identical covariance values Training accuracy (%)	Model with identical covariance values Testing accuracy (%)	Model with different covariance values Training accuracy (%)	Model with different covariance values Testing accuracy (%)
Likert	60.9137	60	61.4213	70
Likert CAN1	58.3756	60	58.8832	60
Likert CAN1 + CAN2	60.9137	60	61.9289	60
fuzzy[a]	*61.4213*	*70*	*62.4365*[b]	*70*[b]
fuzzy CAN1	58.8832	60	58.8832	60
fuzzy CAN1 + CAN2	61.4213	65	62.4365	60

Notes: [a]The best variable for that analytical model; [b]a relatively good classification result; where test results are identical, the training accuracy is used as reference

effectiveness of the model. Accordingly, using the fuzzy scale to directly establish a model yields the best classification model. Classification accuracy is greater than 70 percent regardless whether the normality assumption calls for identical covariance values or different covariance values, but training accuracy is slightly higher with different covariance values than with identical covariance values. For this reason, this datum is adopted as the optimum result for the model.

4.3 Using an ANN to establish a model

Researchers have argued that an ANN model cannot judge whether input variables are representative, or if they have any effect. Our study uses the CFA of SEM to prove that the five input variables selected in the present study (Table II) are all measurement variables that can be used to measure supplier performance classifications. In addition, our study uses a MDA model to prove that these five variables all have good significance in the evaluation and classification of suppliers (Table VI).

Using rigorous statistical methods to assist in confirming the input data of a BPN model should enable the BPN model to yield better output and effectiveness, and by taking advantage of its excellent forecasting and classification capability, we are confident that a better result can be obtained in the establishment of a supplier evaluation model.

We then use PCNeuron 4.0 software to perform analytical comparisons against a single set of sample data. First, the present study divides 217 items of data into 197 items of model construction data and 20 items of model validation data. The content of the data is all identical to the content used by MDA. The 197 items of model construction data are further divided into 177 items of training data and 20 items of testing data. These are used for observing whether the established model is effective, and parameters are adjusted to optimize the model's effectiveness. After the model has been established, we then use the 20 items of validation data to test the model's actual effectiveness and observe how accurately it classifies. Finally, all the most effective ones in the model are selected as the best supplier evaluation model.

We take a Likert scale and a fuzzy scale together with canonical correlation function value conversions (CAN1, CAN1 + CAN2) and plug them into a BPN model to establish a model. The initial model settings are adjusted to the most commonly used values, i.e. the number of learning cycles is set at 300, initial learning rate is set at 1, and initial momentum factor is set at 0.5. Next, the present study first tests the model's effectiveness without adding any hidden layers; if effectiveness is good it means that there is a significant linear relationship between the data in question and it is therefore unnecessary to use an ANN model to establish a model because a regular statistical model will yield better results. However, testing shows that with zero hidden layers there is still room for improvement in classification effectiveness, therefore we added one hidden layer and tested the output results with different numbers of neurons.

Six different measurement scales (Likert, Likert CAN1, Likert CAN1 + CAN2, fuzzy, fuzzy CAN1, fuzzy CAN1 + CAN2) are plugged into a BPN model, and this yields four parameters: optimum number of neurons, optimum number of learning cycles, initial learning rate, and initial momentum factor. We take the optimum parameters for those scales, plug them into the validation model, and observe the classification effectiveness of the validation model. The test results thus obtained are shown in Tables XIII-XXIV.

After multiple tests, the output results for each scale are as set out in Table XXV. The table shows that using Likert or fuzzy input variables yields classification accuracy of 75 and 85 percent, respectively, both of which are better than the 70 percent achieved with MDA. The accuracy achieved with the fuzzy scale is especially satisfactory. Table XXVI shows detailed information on optimum model parameters

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.35025	0.55000	0.24379	0.24832
1	1	0.39086	0.50000	0.24701	0.24784
1	2	0.35025	0.50000	0.23209	0.26170
1	3	0.32487	0.40000	0.22266	0.26262
1 [a]	*4* [a]	*0.31472*	*0.40000*	*0.22289*	*0.26170*
1	5	0.31980	0.45000	0.22161	0.27663
1	6	0.31472	0.55000	0.22204	0.26796
1	7	0.33503	0.50000	0.22517	0.26718
1	8	0.31980	0.50000	0.22333	0.26621
1	9	0.31980	0.40000	0.22052	0.27994
1	10	0.30964	0.50000	0.21986	0.28485

Notes: [a]The optimum values; data in italics represent the optimum parameters

Table XIII. Seeking the optimum number of neurons – Likert scale BPN model

Item	Value
Input variables	5
Output variables	3
Hidden layers	1
Neurons	4
Learning cycles	300
Initial learning rate	1
Initial momentum factor	0.5
Validation accuracy (%)	75
Validation RMS	0.21702

Table XIV. Validation results for Likert scale BPN model

Table XV.
Seeking the optimum number of neurons – Likert CAN1 scale BPN model

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.40678	1.00000	0.24234	0.35033
1	1	0.40678	1.00000	0.24791	0.34968
1 [a]	*2* [a]	*0.39548*	*0.75000*	*0.24295*	*0.30892*
1	3	0.40113	0.80000	0.24425	0.31237
1	4	0.40113	0.90000	0.24451	0.31576
1	5	0.40113	0.75000	0.24391	0.30930
1	6	0.40678	0.75000	0.24516	0.31103
1	7	0.40113	0.80000	0.24507	0.31239
1	8	0.41808	1.00000	0.25224	0.33956
1	9	0.40113	0.85000	0.24748	0.31352
1	10	0.40113	1.00000	0.24963	0.32042

Notes: [a]The optimum values; data in italics represent the optimum parameters

Table XVI.
Validation results for Likert CAN1 scale BPN model

Item	Value
Input variables	1
Output variables	3
Hidden layers	1
Neurons	2
Learning cycles	300
Initial learning rate	1
Initial momentum factor	0.5
Validation accuracy (%)	55
Validation RMS	0.25554

Table XVII.
Seeking the optimum number of neurons – Likert CAN1 + CAN2 scale BPN model

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.37853	1.00000	0.23852	0.35600
1	1	0.40678	1.00000	0.24603	0.35394
1	2	0.38418	0.85000	0.23910	0.32757
1	3	0.37288	0.85000	0.24063	0.32499
1	4	0.38418	0.85000	0.24548	0.31838
1	5	0.37288	0.85000	0.24178	0.32657
1	6	0.37853	0.85000	0.24178	0.32737
1 [a]	*7* [a]	*0.38983*	*0.75000*	*0.24945*	*0.31210*
1	8	0.37853	0.85000	0.24444	0.32652
1	9	0.38983	0.90000	0.24916	0.32752
1	10	0.39548	0.85000	0.24737	0.32215

Notes: [a]The optimum values; data in italics represent the optimum parameters

when the fuzzy scale is used. Table XXVII shows judgment probability output values for the BPN supplier evaluation model. Decision makers can use the BPN supplier evaluation model output probability values to judge which supplier category a given supplier belongs under.

Supplier categories are a type of nominal scale, therefore multi-neuronal coding is used to carry out supplier classification coding, where (0 0 1) represents Class A (0 1 0) represents Class B, and (1 0 0) represents Class C suppliers. For this reason, the BPN model carries three different types of output variables.

Item	Value
Input variables	2
Output variables	3
Hidden layers	1
Neurons	7
Learning cycles	3,000
Initial learning rate	1
Initial momentum factor	0.2
Validation accuracy (%)	55
Validation RMS	0.24838

Table XVIII. Validation results for Likert CAN1 + CAN2 scale BPN model

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.35533	0.55000	0.24417	0.24742
1	1	0.39086	0.50000	0.24755	0.24978
1	2	0.35025	0.50000	0.23220	0.26422
1	3	0.33503	0.55000	0.22520	0.27390
1	4	0.32487	0.45000	0.22246	0.26234
1	5	0.33503	0.40000	0.22302	0.26826
1	6	0.30964	0.55000	0.22050	0.27469
1	7	0.35533	0.55000	0.22614	0.27412
1 [a]	*8* [a]	*0.31980*	*0.45000*	*0.22356*	*0.26236*
1	9	0.30964	0.50000	0.22009	0.378226
1	10	0.33503	0.45000	0.22316	0.26820

Notes: [a]The optimum values; data in italics represent the optimum parameters

Table XIX. Seeking the optimum number of neurons – fuzzy scale BPN model

Item	Value
Input variables	5
Output variables	3
Hidden layers	1
Neurons	8
Learning cycles	5,000
Initial learning rate	0.5
Initial momentum factor	0.2
Validation accuracy (%)	85
Validation RMS	0.18799

Table XX. Validation results for fuzzy scale BPN model

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.40678	1.00000	0.24295	0.34933
1	1	0.40678	1.00000	0.24872	0.34873
1	2	0.39548	0.90000	0.24357	0.30913
1	3	0.39548	0.90000	0.24485	0.31670
1	4	0.40678	1.00000	0.24753	0.33039
1	5	0.40113	0.90000	0.24580	0.31593
1 [a]	*6* [a]	*0.40113*	*0.85000*	*0.24595*	*0.31395*
1	7	0.40113	0.90000	0.24640	0.31481
1	8	0.39548	0.95000	0.24765	0.31666
1	9	0.41808	1.00000	0.25151	0.32707
1	10	0.40678	0.90000	0.25006	0.31351

Notes: [a]The optimum values; data in italics represent the optimum parameters

Table XXI. Seeking the optimum number of neurons – fuzzy CAN1 scale BPN model

Item	Value
Input variables	1
Output variables	3
Hidden layers	1
Neurons	6
Learning cycles	500
Initial learning rate	1
Initial momentum factor	0.6
Validation accuracy (%)	65
Validation RMS	0.24190

Table XXII. Validation results for fuzzy CAN1 scale BPN model

Hidden layers	No. of neurons	Training error rate	Testing error rate	Training RMS	Testing RMS
0	0	0.38418	1.00000	0.23900	0.35559
1	1	0.40678	1.00000	0.24664	0.35365
1 [a]	*2* [a]	*0.37853*	*0.80000*	*0.23966*	*0.31946*
1	3	0.37853	0.85000	0.23959	0.32646
1	4	0.37288	0.80000	0.24215	0.32064
1	5	0.37853	0.85000	0.24200	0.32800
1	6	0.37853	0.85000	0.24198	0.32219
1	7	0.38418	0.85000	0.24153	0.32714
1	8	0.38418	0.85000	0.24337	0.32485
1	9	0.39548	0.95000	0.25225	0.32729
1	10	0.39548	0.85000	0.24734	0.32558

Notes: [a]The optimum values; data in italics represent the optimum parameters

Table XXIII. Seeking the optimum number of neurons – fuzzy CAN1 + CAN2 scale BPN model

5. Conclusions

The optimum parameters for the BPN supplier evaluation model of Table XXVII shows that misjudgments are made for data items 1, 13, and 19. However, the Class C and Class B probabilities for datum 13 are very close (0.528 for Class C and 0.465 for

Class B). If decision makers or auditors were to take the probabilities as points of reference to support the decision-making process, he or she could go an extra step by paying an on-site visit to the supplier represented by datum 13 and do a more careful evaluation, thereby further improving overall judgment accuracy. In Table XXVII,

Item	Value
Input variables	2
Output variables	3
Hidden layers	1
Neurons	2
Learning cycles	300
Initial learning rate	1
Initial momentum factor	0.5
Validation accuracy (%)	65
Validation RMS	0.25180

Table XXIV. Validation results for fuzzy CAN1 + CAN2 scale BPN model

Type of input variable	Training accuracy (%)	Testing accuracy (%)	Validation accuracy (%)
Likert	68.528	60	75
Likert CAN1	60.452	25	55
Likert CAN1 + CAN2	66.102	30	55
fuzzy[a]	*83.756* [b]	*55*	*85* [b]
fuzzy CAN1	59.322	25	65
fuzzy CAN1 + CAN2	62.147	20	65

Notes: [a]The best variable for that analytical model; [b]a relatively good classification result; where validation results are identical, the training accuracy is used as reference

Table XXV. Comparison of BPN classification results

Setting	Value
1. Input processing elements	5
2. 1st hidden layer processing elements	8
3. 2nd hidden layer processing elements	0
4. Output processing elements	3
5. Training samples	197
6. Testing samples	20
7. Learning cycles	5,000
8. Testing cycles	10
9. Use batch learning (yes = 1, no = 0)	0
10. Use weighted values for learned network links (yes = 1, no = 0)	0
11. Weighting range (0.1 ~ 0.5)	0.3
12. Random seed (0.1 ~ 0.9)	0.456
13. Initial learning rate (0.1 ~ 10.0)	0.5
14. Learning rate reduction factor (0.9 ~ 1.0)	0.95
15. Minimum learning rate (0.01 ~ 1.0)	0.1
16. Initial momentum factor (0.0 ~ 0.8)	0.2
17. Momentum factor reduction factor (0.9 ~ 1.0)	0.95
18. Minimum momentum factor (0.0 ~ 0.1)	0.1

Table XXVI. Optimum parameters for BPN supplier evaluation model – fuzzy scale

Table XXVII.
Estimation of probability for BPN supplier evaluation model – fuzzy scale

Case	Actual Class C	Actual Class B	Actual Class A	Predict Class C	Predict Class B	Predict Class A
1	0	0	1	0.556	0.399	0.152
2	0	0	1	0.278	0.429	0.482
3	0	0	1	0.272	0.205	0.748
4	0	0	1	0.139	0.336	0.745
5	0	0	1	0.222	0.358	0.617
6	0	0	1	0.184	0.372	0.650
7	0	0	1	0.149	0.236	0.827
8	0	0	1	0.260	0.223	0.753
9	0	1	0	0.239	0.679	0.261
10	0	1	0	0.232	0.959	0.022
11	0	1	0	0.219	0.736	0.202
12	0	1	0	0.300	0.605	0.265
13	0	1	0	0.528	0.465	0.169
14	0	1	0	0.202	0.518	0.461
15	0	1	0	0.288	0.849	0.081
16	0	1	0	0.405	0.595	0.152
17	0	1	0	0.365	0.600	0.218
18	1	0	0	0.659	0.242	0.220
19	1	0	0	0.262	0.310	0.620
20	1	0	0	0.670	0.147	0.340

a value of 1 in column 1 indicates a Class C supplier, a value of 1 in column 2 indicates a Class B supplier, and a value of 1 in column 3 indicates a Class A supplier. Columns 4-6 represent the probability values of the BPN supplier evaluation model outputs for, Classes C, B, and A suppliers, respectively.

5.1 Theoretical implications

Our study uses the BPN model of ANNs together with CANDISC to perform variable reduction testing and fuzzy scale conversion, and compares it against traditional MDA classification prediction models. Before carrying out model testing, the present study uses SEM to test sample data to prove that the comparison samples and measurement criteria aspects being studied have a statistically good fit and significance. This part of the study is an innovation that has not been attempted in previous research, and deserves to be additionally developed and explored in further studies relating to the science of decision making. One reason for this is that when a novel model is compared against effectiveness of a conventional statistical method rigorous statistical methods are not used to test the chosen samples or criteria aspects in order to determine whether the sample data being studied and compared. When the samples are analyzed under inappropriate conditions and the data are analyzed without being appropriately processed, there is naturally room for doubt regarding the results and findings of the research.

A new paradigm for the science of decision making that the present study attempts to put forward not only includes a combination of several different effective methods of research and analysis, which makes its decision-making model far more effective than traditional methods of statistical analysis, but furthermore, is more rigorous than the previous literature in data preprocessing and validation, and attaches greater importance to these steps, in hopes that the research results obtained will make a greater contribution and be more reliable. In addition, with respect to its research conclusions, although the CANDISC variable reduction method employed by the present study does not actually improve the model's classification accuracy, nevertheless, future studies could still compare the effectiveness of CANDISC and other variable reduction methods, and could also make use of it in other classification models, observing to see whether it can help improve the models' classification accuracy.

With respect to scale conversion, the results of our research indicate that analysis with a fuzzy scale yields higher classification accuracy than with a Likert scale, regardless whether the model is BPN or MDA. It may be that this conclusion is not universally applicable, but future researchers would nevertheless be well advised to consider using a fuzzy scale for measurement when establishing a decision-making model (Munoz *et al.*, 2008). We also argue that using scale conversion does indeed offer the possibility of an improvement in a model's classification effectiveness.

Finally, the results of our study indicate that after samples are put through the steps of SEM and criteria validation, the use of a BPN classification model together with fuzzy scale conversion can yield better classification accuracy than an MDA classification model, which is a traditional statistical method. The new method thus represents a new paradigm for supplier selection that we should try out and pay attention to.

5.2 Managerial implications

As a practical matter, enterprises are faced with a large number of supplier candidates, most of whom they have never dealt with before and are not familiar with. This usually yields many unforeseen risks and detracts from the competitive benefits that otherwise derive from proper utilization of a supply chain. For this reason, enterprises and auditors must make a serious effort to use reliable evaluation criteria for the purpose of effectively selecting appropriate suppliers. However, just relying on the subjective judgments of purchasing personnel does not necessarily meet the need for objective and impartial decision making, and may allow for personal biases, inexperience, and other such factors to adversely affect decisions. There is thus a need to use a set of scientific models to aid in the process of decision-making analysis.

The present study provides a new method of analyzing decision-making models, one that can enable an enterprise and auditor that has amassed a certain quantity of information on suppliers to establish a scientific model for decision-making analysis, and can help enterprises identify appropriate suppliers. The model's output results can also be used as reference in evaluating the appropriateness of suppliers, thus enabling purchasing personnel and auditor to employ a scientific means of selecting suppliers, which will improve the effectiveness of decision making.

An enterprise must keep in mind the scale of its own operations and the diversity of its sources of suppliers when deciding whether or not to establish this scientific decision-making and internal control model. If supplier candidates that need to be analyzed are relatively few in number and easily visited in person, then establishing this type of decision-making and internal control model is not of great use, and the cost would far outstrip the benefits. However, if the supplier group is so large and highly heterodox that there is not enough manpower to carefully review each and every supplier and prepare a list of the most promising candidates, then it is better to use the decision-making analysis and internal control model recommended in the present study to assist in the decision-making and internal control process, as it can enable the user to effectively and quickly identify an appropriate supplier list. Once such a list has been prepared, individuals can make on-site visits or use their judgment to make the final supplier selections. In this manner, it is possible for an enterprise to reap the proverbial "twice the benefit for half the effort" in its SCM thanks to the adoption of an effective supplier selection process.

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Corresponding author
Binshan Lin can be contacted at: binshan.lin@lsus.edu