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Supplier Selection Via Principal Component Analysis: An Empirical Examination

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Abstract: This study presents a multivariate approach for solving supplier selection problem. The approach is based on Principal Component Analysis (PCA) that uses information obtained from eigen values to combined different ratio measures defined by every input and every output.

Key words: Principle component analysis, supply chain, decision making

INTRODUCTION

Supplier selection is one of the most critical activities of purchasing management in a supply chain, because of the key role of supplier's performance on cost, quality, delivery and service in achieving the objectives of a supply chain. Supplier selection is a Multiple Criteria Decision-Making (MCDM) problem which is affected by several conflicting factors. Consequently, a purchasing manager must analyze the trade off among the several criteria. MCDM techniques support the decision-makers DMs in evaluating a set of alternatives. Depending upon the purchasing situations, criteria have varying importance and there is a need to weight criteria (Dulmin and Mininno, 2003). The criticality of supplier selection is evident from its impact on firm performance and more specifically on final product attributes such as cost, design, manufacturability, quality and so forth.

Banker and Khosla (1995) classified the supplier selection process as an important Operations Management (OM) decision area. They suggest that OM research should attempt to identify the supply chain management practices that provide competitive advantage.

Yahya and Kingsman (1999) used Saaty's Analytic Hierarchy Process (AHP) method to determine priority in selecting suppliers. The AHP has found widespread application in decision-making problems, involving multiple criterion systems of many levels. The strongest features of the AHP are that it generates numerical priorities from the subjective knowledge expressed in the estimates of paired comparison matrices. The method is surely useful in evaluating suppliers' weights in marketing, or in ranking order, for instance. It is, however, difficult to determine suitable weight and order of each alternative. Weber (1996) used data envelopment analysis in supplier selection problems especially when multiple conflicting criteria have to be considered. DEA identifies an 'efficient frontier' from the inputs and outputs to be evaluated creating Decision Making Units (DMU's) and then the efficiency of each of these DMUs are compared to the efficient frontier by using identifying the most efficient DMU.

In the present study, an alternative methodology is proposed to aid purchasing managers in identifying and selection suppliers. This approach attempts to address the need for flexible models that are highly customized to meet an individual firm's particular needs. This is a multi-objective approach to supplier selection that attempts to provide a useful decision support system for a purchasing manager faced with multiple suppliers and tradeoffs such as price, delivery reliability and product quality.

PRINCIPLE COMPONENT ANALYSIS

Principal Component Analysis (PCA) is widely used in multivariate statistics such as factor analysis. It is used to reduce the number of variables under study and consequently ranking and analysis of Decision-Making Units (DMUs), such as industries, universities, hospitals, cities, etc (Azadeh *et al.*, 2002, 2003). These DMUs utilize a variety of sources as inputs to produce several outputs. The purpose of another study was to describe and demonstrate the applicability of two multivariate statistical techniques, namely Principal Component Analysis (PCA) and corresponding analysis, as analysis

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tools for quality professional. Using a principal component factor analysis with a rotation technique identifies seven hotels out of 33 hotel attributes and determines the level of satisfaction and service quality of Hong Kong hotels among Asian and Western travelers (Tat and Raymond, 2000). A multivariate analysis proposed a framework for measuring the efficiency of investment in IT that addresses some shortcomings include measurement errors, lags between investment and benefits, redistribution of profits and mismanagement of IT resources. This study suggests the utilization of multivariate technique as an objective optimization approach for the comparative efficiency evaluation of the maintenance department (Kamal *et al.*, 2000). Furthermore, PCA captured the measurement correlations and reconstructed each variable to define associated residuals and sensor validity index. The beverage data was analyzed using PCA and cluster analysis (Rossi and Thomas, 2001). A multivariate analysis was used to test whether there is any relationship between airline flight delays and the financial situation of an airline (Bhat, 1995).

The objective of PCA is to identify a new set of variables such that each new variable, called a principal component, is a linear combination of original variables. Second, the first new variable y_1 accounts for the maximum variance in the sample data and so on. Third, the new variables (principal components) are uncorrelated. PCA is performed by identifying Eigen structure of the covariance or singular value decomposition of the original data. Here, the former approach will be discussed. It is assumed there are p variables (indexes) and k DMUs and suppose $X = (x_1 \ldots x_p)_{k\times p}$ is a k×p matrix composed by x_{ij}'s defined as the value of jth index for ith DMU and therefore $X = (x_{1m} \ldots x_{km})^T$ (m = 1,..., p). Furthermore, suppose $\hat{X} = (\hat{x}_1 \ldots \hat{x}_p)_{k\times p}$ is the standardized matrix of $X = (x_1 \ldots x_p)_{k\times p}$ with $\hat{x}_{ij}$'s defined as the value of jth standardized index for ith DMU and therefore $\hat{x}_m = (\hat{x}_{1m} \ldots \hat{x}_{km})^T$. PCA is performed to identify new independent variables or principal components (defined as Y_j for j = 1…p), which are, respectively different linear combination of $\hat{x}_1 \ldots \hat{x}_p$. As mentioned, this is achieved by identifying eigen structure of the covariance of the original data. The principal components are defined by a k×p matrix $Y = (y_1 \ldots y_p)_{k\times p}$ composed by y_{ij}'s are shown:

$$y_1 = l_{11}\hat{x}_1 + l_{12}\hat{x}_2 + \ldots + l_{1p}\hat{x}_P$$

$$y_2 = l_{21}\hat{x}_1 + l_{22}\hat{x}_2 + \ldots + l_{2p}\hat{x}_P$$

$$\vdots$$

$$y_P = l_{p1}\hat{x}_1 + l_{p2}\hat{x}_2 + \ldots + l_{PP}\hat{x}_P$$

l_{mj} is the coefficient of m-th variable for the jth principal component. The l_{mj}'s are estimated such that the following conditions (1, 2 and 3) are met:

- Y_1 accounts for the maximum variance in the data, Y_2 accounts for the maximum variance that have not been accounted by y_1 and so on

$$l_{m1}^2 + l_{m2}^2 + \ldots + l_{mp}^2 = 1 \quad m = 1 \ldots p \tag{1}$$

$$l_{m1}.l_{n1} + l_{m2}.l_{n2} + \ldots + l_{mp}.l_{np} = 0 \text{ for all } M \neq n,\ n = 1 \ldots p \tag{2}$$

For obtaining the l_{ij}'s and consequently p vectors $(y_{1j} \ldots y_{kj})$ (j = 1…p) and PCA scores the following steps are performed:

Step 1: Calculate the sample mean vector $\bar{x}$ and covariance matrix S:

$$\bar{x} = (\bar{x}_1 \ldots \bar{x}_p)_{1\times p} \tag{3}$$

$$\text{In which, } \bar{x}_j = \frac{1}{k}\sum_{i=1}^{k} x_{ij} \text{ for } j1 \ldots p \tag{4}$$

$$S = (s_{jq})_{p\times p} = \frac{1}{k-1}(X - \bar{x})^T (X - \bar{x}) \text{ for } q\ 1 \ldots p \tag{5}$$

Step 2: Calculate the sample correlation matrix.

$$R = C_1 / \sqrt{s_{jj}}.S.C_1 / \sqrt{s_{jj}} \text{ where } C_1 / \sqrt{s_{jj}} \text{ is a p}$$

p diagonal matrix whose jth diagonal element is $1/\sqrt{s_{jj}}$ for j = 1… p

Step 3: Solve the following equation

$$\left| R - \lambda I_p \right| = 0$$

where, I_p is a p×p identity matrix. We obtain the ordered p characteristic roots (eigenvalues) $\lambda_1 \geq \lambda \geq_2 \ldots \geq \lambda_p$ with $\sum_{j=1}^{p} \lambda_j = p$ and the related p characteristic vectors (eigenvectors) $(l_{m1}, l_{m2}, \ldots, l_{mp})$ (m = 1… p)

Those characteristic vectors compose the principal components Y_i. The components in eigenvectors are respectively the coefficients in each corresponding Y_i:

$$Y_m = \sum_{j=1}^{p} l_{mj}\hat{x}_{ij} \text{ for } m = 1 \ldots p \text{ and } i = 1 \ldots k \tag{6}$$

RESEARCH DESIGN

In this research we use a case study which was illustrated by Narasimhan *et al*. (2001). Five inputs and four outputs are used for analysis in the following approach.

For the purpose of the PCA evaluation, items on the supplier capability Questionnaire were grouped into the following categories, constituting the input variables:

- Quality Management Practices and systems (QMP)
- Documentation and Self-Audit (SA)
- Process/Manufacturing Capability (PMC)
- Management of the firm (MF)
- Cost Reduction capability(CR)

These five categories were measured with a composite score between 0 and 1. the score was computed as the proportion of yes answers to individual questionnaire items in the category. Blank and not applicable responses were not considered in the calculation of the proportion of the yes responses.

Items on the supplier performance Assessment Questionnaire were grouped into the following categories, constituting the output variables:

- Quality
- Price
- Delivery
- Cost Reduction Performance (CRP)

These categories were also measured with a composite score between 0 and 1. To compute the score, the proportion of yes answer was evaluated in each category to provide an objective measure of the variables in the category.

Table 1 shows the scaled composite scores for the input and output variables for the 23 suppliers in order to maintain confidentiality the data were have scaled by dividing each factor by its factor mean score.

Twenty output/input ratios for the supplier's attributes were defined:

d1 = Quality/QMP
d2 = Quality/SA
d3 = Quality/PMC
d4 = Quality/Mgt.
d5 = Quality/CR
d6 = Price/QMP
d7 = Price/SA
d8 = Price/PMC
d9 = Price/Mgt.
d10 = Price/CR
….
d19 = CRP/Mgt.
d20 = CRP/CR

The decision maker would like to select the supplier that provides the best combination of the performance parameters. In statistical terms, these supplier s are extreme observations that lie away from the data. Thus, a

Table 1: Data matrix for inputs and outputs

Supplier	QMP	SA	PMC	Mgt.	CR	Quality	Price	Delivery	CRP
2	0.9662	0.9742	1.0385	1.0808	0.7839	0.6211	0.8922	0.1284	1.2107
3	0.7054	1.0438	0.7500	0.8782	0.8750	0.6932	0.8922	0.3855	0.0000
5	0.5611	0.8947	0.7789	0.7205	0.7404	1.0205	0.4341	1.5420	0.0000
6	1.1272	1.0438	0.9520	0.9607	1.1402	1.6639	1.1333	1.5420	1.2107
9	1.1272	1.0438	1.1251	1.0808	1.2115	0.9983	1.3503	1.1565	1.2107
10	0.9877	1.0438	0.9376	1.0808	0.9422	1.0426	1.3263	1.7990	2.4214
11	0.8051	0.8351	1.0385	0.9607	1.0768	1.2201	1.2056	0.7710	2.4214
12	1.1809	1.0438	1.1251	1.0208	1.0096	0.8429	1.1333	0.6424	1.2107
13	1.2346	1.0438	1.1251	1.0808	1.1442	0.6433	0.8922	0.3855	0.0000
16	0.5904	1.0438	0.6058	0.7629	0.4038	1.4419	0.4341	1.4135	0.0000
17	0.8642	0.8118	0.8182	0.9536	0.8076	0.4215	0.8922	1.0279	0.0000
20	0.6441	0.8351	1.0227	1.0208	1.0768	1.0205	1.3263	0.7710	1.2107
22	1.2346	1.0438	1.1251	1.0808	1.2115	0.5546	1.1092	1.0279	1.2107
23	1.0662	1.0438	1.1251	1.0808	1.2115	0.8208	0.8922	0.8994	1.2107
24	1.0100	1.0438	0.8654	1.0208	0.6815	1.2423	1.5674	1.4135	2.4214
25	0.8978	0.9742	1.0385	1.0208	0.8076	1.0205	0.8922	0.3855	0.0000
26	1.1272	0.9742	1.0385	1.0208	1.0768	1.0205	0.8681	0.7710	0.0000
28	1.1809	1.0438	1.1251	1.0808	1.2115	1.2201	0.2411	0.0000	0.0000
29	1.0735	1.0438	1.1251	0.9007	0.9422	1.1647	0.8922	1.4135	1.2107
31	1.0735	1.0438	1.1251	1.0808	1.1442	0.8429	1.0550	1.4135	1.2107
32	1.2346	1.0438	1.1251	1.0133	1.2115	0.7764	0.8922	1.0279	0.9540
33	1.2346	1.0438	0.9520	1.0808	1.2115	1.4642	1.3263	1.7990	1.4839
35	1.0735	1.0438	1.0385	1.0172	1.0768	1.2423	1.3503	1.2849	1.5900

Table 2: Correlations between output/input ratios

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12	d13	d14	d15	d16	d17	d18	d19	d20
d1	1.000	0.797**	0.893**	0.888**	0.855**	0.207	0.117	0.023	0.05	0.124	0.677**	0.390*	0.570**	0.527**	0.665**	0.086	0.038	0.030	0.019	0.01
d2	0.797**	1.000	0.835**	0.916**	0.631**	0.216	0.130	0.179	0.178	0.151	0.439*	0.405*	0.450*	0.446*	0.420*	0.324	0.308	0.308	0.309	0.250
d3	0.893**	0.835**	1.000	0.949**	0.913**	0.065	0.115	0.140	0.017	0.215	0.625**	0.466*	0.670**	0.590**	0.736**	0.067	0.062	0.118	0.079	0.090
d4	0.888**	0.916**	0.949**	1.000	0.819**	0.020	0.133	0.036	0.000	0.087	0.601**	0.464*	0.610**	0.549**	0.636**	0.095	0.093	0.121	0.116	0.090
d5	0.855**	0.631**	0.913**	0.819**	1.000	0.008	0.231	0.022	0.110	0.265	0.589**	0.335	0.610**	0.500**	0.793**	0.000	0.041	0.011	0.026	0.040
d6	0.207	0.216	0.065	0.020	0.008	1.000	0.871**	0.821**	0.829**	0.714**	0.198	0.274	0.160	0.135	0.093	0.681**	0.617**	0.591**	0.578**	0.570**
d7	0.117	0.130	0.100	0.133	0.231	0.871**	1.000	0.885**	0.949**	0.719**	0.021	0.303	0.100	0.096	0.040	0.758**	0.745**	0732**	0.728**	0.690**
d8	0.023	0.179	0.140	0.036	0.022	0.821**	0.885**	1.000	0.944**	0.876**	0.198	0.433*	0.350	0.279	0.233	0.656**	0.655**	0.721**	0.665**	0.710**
d9	0.052	0.178	0.017	0.000	0.113	0.829**	0.949**	0.94**	1.000	0.789**	0.128	0.409*	0.240	0.246	0.099	0.730**	0.737**	0.758**	0.79**	0.730**
d10	0.124	0.151	0.215	0.087	0.265	0.714**	0.719**	0.876**	0.789**	1.000	0.217	0.326	0.340	0.243	0.363*	0.602**	0.586**	0.674**	0.607**	0.750**
d11	0.677**	0.439*	0.625**	0.601**	0.589**	0.198	0.021	0.198	0.128	0.217	1.000	0.877**	0.940**	0.943**	0.901**	0.132	0.123	0.170	0.140	0.140
d12	0.390*	0.405*	0.466*	0.464*	0.335	0.274	0.303	0.433*	0.409*	0.326	0.877**	1.000	0.930**	0.962**	0.780**	0.324	0.350	0.412*	0.387	0.340
d13	0.569**	0.453*	0.674**	0.605**	0.605**	0.164	0.104	0.343	0.245	0.336	0.936**	0.934**	1.000	0.967**	0.934**	0.177	0.197	0.285	0.236	0.240
d14	0.527**	0.446*	0.590**	0.594**	0.500**	0.135	0.096	0.279	0.246	0.243	0.943**	0.962**	0.970**	1.000	0.873**	0.186	0.212	0.279	0.257	0.230
d15	0.665**	0.420*	0.736**	0.636**	0.793**	0.093	0.044	0.223	0.099	0.363*	0.901**	0.780**	0.930**	0.873**	1.000	0.090	0.094	0.176	0.12	0.180
d16	0.086	0.324	0.067	0.095	0.024	0.681**	0.758**	0.656**	0.730**	0.602**	0.132	0.324	0.180	0.186	0.090	1.000	0.990**	0.961**	0.974**	0.930**
d17	0.038	0.308	0.062	0.093	0.041	0.617**	0.745**	0.655**	0.737**	0.586**	0.123	0.350	0.200	0.212	0.094	0.990**	1.000	0.976**	0.992**	0.940**
d18	0.030	0.308	0.118	0.121	0.011	0.591**	0.732**	0.721**	0.758**	0.674**	0.170	0.412*	0.290	0.279	0.176	0.961**	0.976**	1.000	0.986**	0.980**
d19	0.019	0.309	0.079	0.116	0.026	0.578**	0.728**	0.665**	0.749**	0.607**	0.140	0.387*	0.240	0.257	0.129	0.974**	0.992**	0.986**	1.000	0.950**
d20	0.011	0.246	0.095	0.086	0.045	0.570**	0.689**	0.706**	0.727**	0.747**	0.136	0.340	0.240	0.229	0.183	0.929**	0.937**	0.977**	0.954**	1.000

**Correlation is significant at the 0.01 level (1-trailed), *Correlation is significant at the 0.05 level (1-trailed)

procedure that identifies outlying suppliers regardless of the importance the purchasing manager attaches to each performance parameter of the supplier. Most of the variability in the data set is contained in the first few linear combinations of variables, i.e., the principal components. In other words, PCA is employed to identify the principal components that are respectively, different linear combinations of the performance variables so that the principal components can be multiplied by their Eigen values to obtain a weighted measure of the variables.

The first step in PCA consists of testing whether the variables show a sufficient level of correlation. To this extern; both the correlation matrix (Table 2) and the Bartlett's test of sphericity have been analyzed. The coefficients are the usual Pearson correlations (one-tailed) and confirm that significant correlations can be found.

Bartlett's test of sphericity is a useful instrument to test the null hypothesis that the correlation matrix is an identity matrix. If the null hypothesis cannot be rejected and the sample size is reasonably large the decision maker should reconsider the use of multivariate analysis since the dependent variables are not correlated. In this case, the null hypothesis is rejected at the 0.001 level.

A rule-of-thumb for determining the number of components to extract is to consider the Eigen value greater than one criterion. The so-called Eigen value screen plot is often useful in graphically determining the number of factors extracted (Fig. 1). In the present analysis, four component are a workable solution (since the residual components have all Eigen value less than 1).

Component 1, 2, 3 and 4 account for approximately 0.93 % of the total variance of the variable (Table 3).

The percentage of variance explained by each component represents its relative importance.

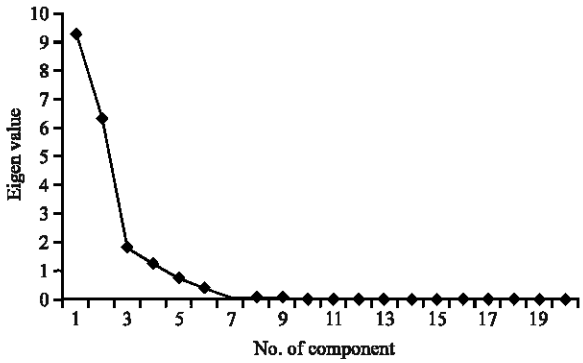

Fig. 1: Eigen values versus component

Table 3: Total variance explained by the components weights of the rotated component

Component	Total	Variance (%)	Cumulative (%)
1	9.2695	46.3477	46.3477
2	6.3202	31.6012	77.9489
3	1.8059	9.0295	86.9784
4	1.2259	6.1295	93.1079
5	0.7197	3.5985	96.7064
6	0.4067	2.0335	98.7399
7	0.0868	0.434	99.1739
8	0.0769	0.3845	99.5584
9	0.0605	0.3025	99.8609
10	0.0133	0.0665	99.9274
11	0.0052	0.026	99.9534
12	0.0042	0.021	99.9744
13	0.0023	0.0115	99.9859
14	0.0012	0.006	99.9919
15	0.0009	0.0045	99.9964
16	0.0004	0.002	99.9984
17	0.0002	0.001	1
18	0.0001	0.0005	1
19	0	0	1
20	0	0	1

The term rotated component in the heading in Table 4 is due to the fact that an orthogonal rotation is usually carried out on the component that are initially extracted. Usually the initial component extraction does

not give interpretable results. One of the purposes of rotation is to obtain components that can be named and interpreted more clearly. in other words rotation makes the larger loadings of the different variables on each component larger than before and smaller loadings smaller than before. There are a number of different methods of extraction-here the varimax method has been chosen. The rotated loadings of each variable on each component are reported in Table 4.

The interpretation of the Table 4 leads the decision maker to conclude that component 1 loads on matters concerning cost reduction performance, component 2 loads on matters concerning quality, component 3 loads on matters concerning delivery and component 4 loads on matters concerning price.

Table 4: Matrix of components (loading smaller than 0.1 are omitted)

	Components			
Variable	1	2	3	4
d1		0.907	0.295	
d2	0.293	0.870	0.127	
d3		0.911	0.360	
d4		0.913	0.318	
d5	-0.122	0.853	0.338	
d6	0.318			0.862
d7	0.507	-0.145		0.804
d8	0.384		0.197	0.871
d9	0.497		0.136	0.812
d10	0.331	0.123	0.169	0.813
d11		0.375	0.887	
d12	0.249	0.147	0.914	0.173
d13		0.351	0.916	0.131
d14	0.138	0.283	0.935	
d15		0.473	0.826	
d16	0.902			0.382
d17	0.929			0.341
d18	0.905		0.145	0.377
d19	0.933		0.112	0.329
d20	0.865		0.108	0.397

Table 5: Final ranking of suppliers

Supplier No.	Score
19	0.462703
18	0.455648
17	0.451472
16	0.441471
20	0.434994
2	0.422197
3	0.320393
4	0.317233
1	0.313260
9	0.292400
10	0.257373
12	0.254993
8	0.249151
5	0.243534
7	0.238442
14	0.237817
15	0.224057
13	0.201660
6	0.200222
11	0.198596

For each variable considered (d_1, d_2, d_3, ..., d_{20}), a coefficient W_i (i = 1 to 20) is obtained by multiplying the loadings on each component by the percentage of variance explained by the component For instance, W_i is obtained as follows:

$$W_i = 0\times0.463477+0.907\times0.316012+0.295 \times0.090295+0\times0.061295 = 0.31326$$

The coefficient is then multiplied by the value of the corresponding variable (d_1 to d_{20}) for each supplier to get final supplier score (Table 5). Based on these score the final ranking is obtained.

Summing up, supplier number 19 ends up as the supplier that provides the best performances with respect to the three component identified.

CONCLUSION

This study describes a multiple-attribute approach based on the use of principal component analysis, aimed at helping purchasing managers to formulate viable sourcing strategies in the changing marketplace. An application of the methodology using actual data retrieved from a firm operating in the bottling industry is illustrated. PCA has proved to be capable of handling multiple conflicting attributes inherent in supplier selection criteria.

PCA's strength is in simultaneously considering multiple inputs and multiple outputs without any need for a priori assignment of weights. PCA also has distinct advantage over the traditional methods of selection suppliers 'performances in that it is not necessary to state the performance measures in the same units. The relevant attributes of suppliers can in fact be measured in any unit such as money, percentages and qualitative subjective judgments. Furthermore since PCA does not force the decision maker into a standardized rating for the attributes this technique is less subjective than the traditional methods.

REFERENCES

Azadeh, M.A. and V. Ebrahimipour, 2002. An integrated approach for assessment of manufacturing sectors based on machine performance: The cases of automotive and food and beverages industries. Proceeding of the 2nd International Conference Manufacturing Complexity, April 9-10, University of Cambridge, UK., pp: 1-11.

Azadeh, M.A., V. Ebrahimipour and G.H. Ataei, 2003. A total machine productivity model for assessment and improvement of electrical manufacturing systems. Proceeding of the 32nd International Conference Computer Indust. Eng., August 11-13, Ireland, pp: 218-227.

Banker, R.D. and I.S. Khosla, 1995. Economics of operations management: A research perspective. J. Operat. Manage., 12: 423-435.

Bhat, V.N., 1995. A multivariate analysis of airline flight delays. Intern. J. Qual. Relia., 12: 230-240.

Dulmin, R. and V. Mininno, 2003. Supplier selection using a multi-criteria decision aid method. J. Purchase Supp. Manage., 9: 177-187.

Kamal, M., Al-Subhi and Al-Harbi, 2000. Optimization of staff numbers in the process industries: An application of DEA. Int. J. Manpower., 21: 47-60.

Narasimhan, R., S. Talluri and D. Mendez, 2001. Supplier evaluation and rationalization via data envelopment analysis: An empirical examination. J. Supp. Chain Manage., 37: 28-37.

Rossi, F. and A.A. Thomas, 2001. Analysis of the beverage data using cluster analysis: Rotated principal components analysis and loess curves. Food Qual. Prefer., 12: 437-445.

Tat, Y. and Raymond., 2000. Levels of satisfaction among Asian and western travelers. Int. J. qual. Reliability Manage., 17: 116-132.

Weber, C.A., 1996. A data envelopment analysis approach to measuring vendor performance. Supp. Chain Manage., 1: 28-39.

Yahya, S. and B. Kingsman, 1999. Vendor rating for an entrepreneur development program: a case study using the analytic hierarchy process method. J. Operat. Res. Soc., 50: 916-930.