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To identify or not to identify: A weighted multidimensional scaling in identifying the similarities of e-shopping stores

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While many studies have discussed the purchase behavior for e-shopping stores, there is little study focusing on mechanism which consumers accurately and reasonably identify the similarities of e-shopping stores. Therefore, we introduce the approach which combines DEMATEL with ANP to modify multidimensional scaling to address this concern. In traditional MDS, the average summation is combined with the proximity matrices of the objects for each criterion (perceived price of stores), which may neglect the interdependence and feedback relationships between the criteria. The weights and relationships of different criteria are treated as equal and independent to obtain similarities that are often counterintuitive because the human mind has a much more complex judgment system that is able to account for different weighting. To address these problems, we propose an approach that combines DEMATEL with ANP. An empirical study is used to compare our approach with traditional MDS.

Key words: Multidimensional scaling (MDS), Analytic network process (ANP), Decision Making Trial and Evaluation Laboratory (DEMATEL), multiple criteria decision making (MCDM), Purchase intention, online shopping.

INTRODUCTION

Electronic commerce in recent years has experienced rapid growth, and online purchases have become popular in a virtual world (Lwin and Williams, 2006; Hashim et al., 2010). To successfully attract online consumers and benefit from doing so, a manager of e-shopping store must know in depth about consumers' perception for differences of his competitors to attack the target market. Previous research regarding consumers' perception, such as purchase intention, has examined products or websites characterized through the interactions between buyers and sellers or through the attitude or perceptions of the buyers themselves (Chang and Lin, 2010; Meng et al., 2011; Tsai, 2010; Wu et al. (2010). For example, much of the previous research has examined purchase intention from various angles such as relationship quality (Gyau and Spiller, 2007; Hu et al., 2010; Wang and Yang, 2010),

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the technology acceptance model (Jahangir and Begum, 2008; Yusoff et al., 2010), and the theory of planned behavior (Chen and Li, 2010; Öze and Yilmaz, 2011); however, the mechanism and process which consumers accurately and reasonably evaluate the similarities of e-shopping stores (low price characteristic of stores) have not been adequately addressed in the literature. To this end, Huang et al. (2005) has proposed that the weights of different criteria (perceived price of stores) in multidimensional scaling (MDS) has received little attention in identifying the similarities of objects (e-shopping stores). The strong emphasis on “similarities” in the previous statement denotes a serious shortcoming in the human judgments (Chen et al., 2008). That is, with rare exception (Varela and Landis, 2010; Westman et al., 2011), and even in the top journal for online consumers’ perception study (Kim et al., 2011), the weights of criteria in MDS have remained to be treated as equal. We examine this concern in the present study to yield a wealth of knowledge for social science field because the fundamental assumption for unequal weights of criteria in MDS that underlies this cumulative knowledge has remained relatively unexamined. For practical development, the issue that underlies this concern is not trivial because the notion of human judgments in identifying characteristics of e-shopping stores is a prominent cue for consumers to choose which the preferred stores are. The goal of this this study is, therefore, to propose a different mechanism to modify MDS by including DEMATEL with ANP approach to accurately and reasonably identify the similarities of e-shopping stores.

Multidimensional scaling (MDS) has been extensively applied in academic and practical fields, but the issue of the weights of different criteria has received little attention (Huang et al., 2005; Chen et al., 2008). In particular, interdependent and feedback relations of criteria are usually ignored during the evaluation process. In the recent development of MDS, however, although Weighted Multidimensional Scaling (WMDS) algorithm has been addressed for the Time of Arrival (TOA) of sensor location (Vo et al., 2008) and mobile location (Wei et al., 2008), it does not focus on the different weights of criteria but the while noises to obtain more accurate location information from the sensors. Therefore, this article proposes an approach that combines the Decision Making Trial and Evaluation Laboratory (DEMATEL) with the Analytic Network Process (ANP) procedure to address the problems of interdependence, feedback, and unequal weights.

The ANP was proposed by Saaty (1996) to overcome the restrictions of interdependence and feedback between criteria for the Analytic Hierarchy Process (AHP). Although ANP can address the problems of interrelation and unequal weights in MDS, the normalization process and the effect of feedback are not ideal. The initial step in the ANP procedure is to compare the criteria with some criterion in the whole system to form an unweighted supermatrix. Then, a weighted supermatrix (normalized matrix) is derived by transforming each column to sum exactly to unity (1.00) from pair-wise comparison matrices. Each element in a column is divided by the number of clusters (e.g., the cluster signifies that some criteria like the measured reliability item in Figure 5) that derive from the same concept (e.g., the measured service quality construct in Figure 5) are included in it), so each column will sum to unity exactly. In the traditional ANP procedure, equal degrees of influence were used to obtain the weighted supermatrix. However, it seems irrational to use equal influence between clusters to obtain the weighted supermatrix because the degrees of influence from one cluster to the others may be different. Second, the feedback assumption may also be flawed because we can assume that the cluster has the effect of feedback or ignore it by subjective judgment in the traditional ANP procedure. To deal with these two problems, we include the DEMATEL approach to modify the ANP procedure.

The DEMATEL approach is used for detecting the interrelation between criteria, and to find the key central criteria to represent the relative effectiveness of different criteria (Warfield, 1976). Using DEMATEL, we can determine the different degrees of influence between clusters and decide if the cluster feedback in the ANP procedure. By combining the DEMATEL approach with ANP, we can obtain a more realistic determination of the degrees of influence of clusters to normalize the unweighted supermatrix in the ANP procedure. By combining DEMATEL with ANP, we can modify the weights of criteria to construct more realistic proximity matrices for MDS analysis. In addition, we demonstrate an empirical study to simulate our proposed approach. The final results are notably different from the traditional MDS analysis.

THE TRADITIONAL MDS APPROACH

Multidimensional scaling (MDS) analysis is used to provide a visual representation of data that can be scanned at a glance by constructing low-dimensional configuration from the pair-wise comparison of similarities between objects. The similarities can be obtained by Euclidean distance or other weighted Euclidean distance (Okada and Imaizumi, 1986) to form a proximity matrix. The proximity matrix can be obtained from seeing how many grades of similarity exist between two objects based on some criterion. Then, by taking the average sum of the proximity matrices for each criterion, we can obtain an average summation proximity matrix for use in MDS analysis. In general, the goal of MDS is to visually reflect the underlying structure of objects by detecting significant underlying dimensions (Mead, 1992).

The advantage of this technique is that we can more clearly and easily determine the difference between the objects. In the traditional MDS procedure, we do not need to understand which criterion is more important than the others, and usually the weights and interrelation of all criteria are treated as equal and independent. This may cause two problems. First, it is difficult for an individual to quantify a precise value in a complex system; however, we can use the ANP approach to divide the whole system into subsystems that can be easily evaluated to obtain the grades of all subsystems. Then, we can integrate the grades into MDS proximity matrix. Second, it seems rational to average the grades of similarities of the objects under each criterion, but the weights among these criteria may be different. It is clear that any set of criteria may have interdependence and feedback. In particular, the weights of all criteria are different. As aforementioned, the evaluation process might become biased if we treat the weights and interrelation of all criteria as equal and independent. For these two problems, the proposed approach that combines DEMATEL with the ANP procedure can be used to overcome these issues to obtain a more proper evaluation for MDS analysis.

The DEMATEL technique

The DEMATEL technique has been used to illuminate specific and intertwined phenomena and contribute to the recognition of practical solutions through a hierarchical structure. According to the concrete criteria of objects, we can verify interdependence among factors and construct the interrelation between criteria to build an impact-relation map (IRM) (Warfield, 1976; Liang et al., 2010; Shih, 2010).

The DEMATEL approach can be stated as following four steps. In the first step, we calculate the average direct influence matrix *D* by scores. In this step, respondents are asked to judge the degree of direct influence of one criterion on the others on a scale 0, 1, 2, 3 and 4, where zero corresponds to no influence, and four to very high influence. Each respondent produces a direct influence matrix, and then an average direct influence matrix *D* is derived from the mean of the direct matrix of each respondent. A simple structure graph between the criteria of the system can be portrayed as Figure 1. For example, an arrow from *b* to *c* signifies that the degree of influence that *b* affects *c* is 3. The degree of influence is the direct effect from factor *i* to factor *j*, as denoted by d_{ij}

The interrelation of impact between criteria can be denoted as average direct influence matrix *D*, as Equation (1).

$$\boldsymbol{D}=\begin{bmatrix} d_{11} & \cdots & d_{1j} & \cdots & d_{1n} \\ \vdots & & \vdots & & \vdots \\ d_{i1} & \cdots & d_{ij} & \cdots & d_{in} \\ \vdots & & \vdots & & \vdots \\ d_{n1} & \cdots & d_{nj} & \cdots & d_{nn} \end{bmatrix} \tag{1}$$

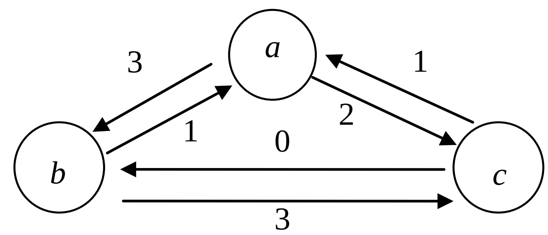

Figure 1. The impact graph.

where the d_{ij} denote the degree of influence from the each criterion of *i*-th row to each criterion of *j*-th column.

In the second step, the initial direct influence matrix ***X*** is obtained by normalizing the average direct influence matrix ***D*** in Equation (1). Specifically, the matrix can be obtained through Equations (2) and (3), and in which all principal diagonal elements are equal to zero.

$$\boldsymbol{X}=s\cdot\boldsymbol{D}$$

$$s=\min\left\{1/\max_i\sum_{j=1}^{n}d_{ij},\ 1/\max_j\sum_{i=1}^{n}d_{ij}\right\} \tag{3}$$

In third step, we obtain the total direct/indirect influence matrix ***T***. A continuous decrease of the indirect effects are powers of ***X*** ($\boldsymbol{X}^2,\boldsymbol{X}^3,...,\boldsymbol{X}^k$ and $\lim_{k\to\infty}\boldsymbol{X}^k=[0]_{n\times n}$, where $\boldsymbol{X}=[d_{ij}^{\ s}]$, $0\le d_{ij}^{\ s}<1$, $0<\sum_{j=1}^{n}d_{ij}^{\ s}\le 1$, $0<\sum_{i=1}^{n}d_{ij}^{\ s}\le 1$. If at least one row or column of the summation, but not all, is equal to 1, then $\lim_{k\to\infty}\boldsymbol{X}^k=[0]_{n\times n}$. The total- influence matrix is given by Equation(4).

$$\boldsymbol{T}=\boldsymbol{X}+\boldsymbol{X}^2+\cdots+\boldsymbol{X}^k$$
$$=[\boldsymbol{X}(\boldsymbol{I}+\boldsymbol{X}+\boldsymbol{X}^2+\cdots+\boldsymbol{X}^{k-1})](\boldsymbol{I}-\boldsymbol{X})(\boldsymbol{I}-\boldsymbol{X})^{-1}$$
$$=\boldsymbol{X}(\boldsymbol{I}-\boldsymbol{X}^k)(\boldsymbol{I}-\boldsymbol{X})^{-1}$$

then $\boldsymbol{T}=\boldsymbol{X}(\boldsymbol{I}-\boldsymbol{X})^{-1}$, when $\lim_{k\to\infty}\boldsymbol{X}^k=[0]_{n\times n}$, (4)

where ***I*** denotes the identity matrix, and we can obtain $\boldsymbol{T}=[t_{ij}]_{n\times n}$, $i,j=1,2,...,n$.

In addition, the approach presents each row sum and column sum of the matrix ***T***, as in Equations (5) and (6).

$$\boldsymbol{r}=(r_i)_{n\times 1}=[\sum_{j=1}^{n}t_{ij}]_{n\times 1} \tag{5}$$

$$\boldsymbol{c}=(c_j)_{n\times 1}=(c_j)'_{1\times n}=[\sum_{i=1}^{n}t_{ij}]'_{1\times n} \tag{6}$$

where r_i denotes the row sum of the i-th row of the matrix $\boldsymbol{T}$ and shows the sum of the direct and indirect effects from a factor i to the other factors. Similarly, c_j denotes the column sum of the j-th column of the matrix $\boldsymbol{T}$ and shows the sum of direct and indirect effects that a factor j has received from the other factors. From Equations (5) and (6), we can obtain the total relative importance of each factor to detect which is the most powerful factor. In addition, when $t_{ii} \neq 0$, it signifies that the factor i has the effect of feedback.

Through the first step to third step, we obtain the IRM matrix T, shown in Equation (7). From the IRM matrix T, we can see the degree of influence from factor i to factor j and decide if the factor i has the effect of feedback (if the t_{ii} is not equal to zero, it signifies that the factor i has the effect of feedback).

$$\boldsymbol{T} = \begin{bmatrix} t_{11} & \cdots & t_{1j} & \cdots & t_{1n} \\ \vdots & & \vdots & & \vdots \\ t_{i1} & \cdots & t_{ij} & \cdots & t_{in} \\ \vdots & & \vdots & & \vdots \\ t_{n1} & \cdots & t_{nj} & \cdots & t_{nn} \end{bmatrix} \tag{7}$$

The ANP technique

The ANP is the general form of AHP to release the restriction of hierarchical structure and interrelation between criteria which has been applied in many fields (Sreekumar and Mahapatra, 2009; Liu, 2010; Lin and Yahalom, 2010; Nuhodzic et al., 2010; Pirannejad et al., 2010; Yang et al., 2010). The approach can be described by the following steps. In the first step, we compare the criteria of the whole system to form the supermatrix. The original supermatrix of column eigenvectors is obtained from pair-wise comparison matrices of criteria by seeing if a criterion has a larger or smaller impact compared to another criterion from the perspective of some third criterion. The relative importance value can be signified using a scale of 1 to 9 to represent equal importance to extreme importance (Saaty, 1996). The general form of the supermatrix is seen in Equation (8).

$$\boldsymbol{W} = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & & C_n \\ e_{11}\ldots e_{1m_1} & e_{21}\ldots e_{2m_2} & \cdots\cdots & e_{n1}\ldots e_{nm_n} \end{array} \\ \begin{array}{cc} C_1 & \begin{array}{c} e_{11} \\ e_{12} \\ \vdots \\ e_{1m_1} \end{array} \\ C_2 & \begin{array}{c} e_{21} \\ e_{22} \\ \vdots \\ e_{2m_2} \end{array} \\ \vdots & \vdots \\ C_n & \begin{array}{c} e_{n1} \\ e_{n2} \\ \vdots \\ e_{nm_n} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{W}_{11} & \boldsymbol{W}_{12} & \cdots & \boldsymbol{W}_{1n} \\ \boldsymbol{W}_{12} & \boldsymbol{W}_{22} & \cdots & \boldsymbol{W}_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ \boldsymbol{W}_{n1} & \boldsymbol{W}_{n2} & \cdots & \boldsymbol{W}_{nn} \end{bmatrix} \end{array} \tag{8}$$

where C_n denotes the n-th cluster, e_{nm} denotes the m-th criterion in the n-th cluster, and $\boldsymbol{W}_{ij}$ is the principal eigenvector of influence of the criteria compared from the j-th cluster to the i-th cluster. In addition, if the j-th cluster has no influence on the i-th cluster, the grade of $\boldsymbol{W}_{ij}$ is equal to zero.

After forming the supermatrix, the weighted supermatrix is derived by transforming all columns sum to unity exactly. This process is similar to the concept of a Markov chain for ensuring the sum of the probabilities of column equal one. Because the row of matrix $\boldsymbol{W}$ has n clusters, each criterion in each column is divided by n to form a weighted matrix (normalized matrix) $\boldsymbol{W}_w$, as in Equation (9). Then, by the Equation (10), we limit the weighted supermatrix $\boldsymbol{W}_w$ by raising it to a sufficiently large power k, until the supermatrix has converged and become a long-term stable supermatrix with global priority vectors.

$$\boldsymbol{W}_w = \begin{bmatrix} \boldsymbol{W}_{11}/n & \boldsymbol{W}_{12}/n & \cdots & \boldsymbol{W}_{1n}/n \\ \boldsymbol{W}_{12}/n & \boldsymbol{W}_{22}/n & \cdots & \boldsymbol{W}_{2n}/n \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ \boldsymbol{W}_{n1}/n & \boldsymbol{W}_{n2}/n & \cdots & \boldsymbol{W}_{nn}/n \end{bmatrix} \tag{9}$$

$$\lim_{k\to\infty} \boldsymbol{W}_w^k \tag{10}$$

By using this normalized process, as shown in Equation (9), it implies that there are the same degrees of influence between clusters (it signifies that the degree of influence from cluster j to cluster i is $1/n$, for $i \neq j$, and vice versa). However, we know that the influence from one cluster to the others may be different. Therefore, using the assumption of equal degree for different clusters to obtain the weighted supermatrix is not ideal. Additionally, the effect of feedback in each cluster is not addressed by this approach. This article adopts the DEMATEL approach to solve these problems.

THE HYBRID MCDM MODEL

In terms of online product, nevertheless, the mechanism of consumers' decision can be further decomposed into two stages (that is, before the purchase and after the

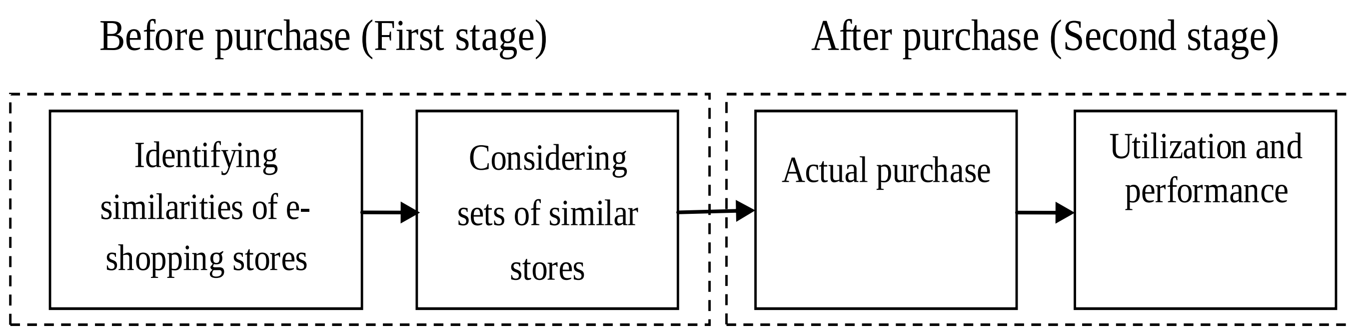

Figure 2. Conceptual model of consumer behavior.

purchase), as shown in Figure 2. First, the characteristics (perceived price) of stores cause consumers to identify the similarities of e-shopping stores as considering sets of similar stores (first stage) that consequently leads to actual purchase (second stage). Based on the conceptual model above (Figure 2), this study focuses on the first stage (that is, before purchase) by combining DEMATEL with ANP into MDS to accurately and reasonably identify the similarities of e-shopping stores. The combing approach proposed by this study is presented and explained in detail in the following.

The preferences in combining DEMATEL with ANP approach are essentially human judgments based on one's perception, and we believe the combining approach allows for an accurate and reasonable description of the decision making process. The primary focus of this article is to combine DEMATEL with ANP to modify MDS, which, in turn, to identify the similarities and preferences of objects (e-shopping stores) in terms of the axes of the space, which represent perceived attributes and characterize those objects. By doing so, the visual dimensionality and configuration or pattern of objects whose weighted distance structure best fits the input data can be obtained and explained easily. In sum, the combining approach provides three advantages for decision-makers: (1) a clear snapshot of objects could be easily obtained; (2) the reduced dimensions, after clearly explained and labeled, could be treated as a mental shortcut for decision-makers in the future; (3) distinct bojectses clusters could be obtained easily based on the measure of psychological distances.

According to above statements, we propose a hybrid MCDM model that combines DEMATEL and ANP for evaluating and improving the issues discussed in the first three sections to modify the MDS procedure. First, we use the DEMATEL approach to build the IRM. Next, we use the total-influence matrix $\boldsymbol{T}$, shown in Equation (11), and generate a new normalized matrix $\boldsymbol{T}_n$, shown in Equation (12). First we assume that the $t_{ii} \neq 0$ to support the assumption of feedback $(\boldsymbol{W}_{ii} \neq 0)$ in ANP procedure

$$d_i = \sum_{j=1}^{n} t_{ij}$$

$$\boldsymbol{T} = \begin{bmatrix} t_{11} & \cdots & t_{1j} & \cdots & t_{1n} \\ \vdots & & \vdots & & \vdots \\ t_{i1} & \cdots & t_{ij} & \cdots & t_{in} \\ \vdots & & \vdots & & \vdots \\ t_{n1} & \cdots & t_{nj} & \cdots & t_{nn} \end{bmatrix} \quad d_1 = \sum_{j=1}^{n} t_{1j}^{\alpha} \tag{11}$$

$$\boldsymbol{T}_n = \begin{bmatrix} t_{11}/d_1 & \cdots & t_{1j}/d_1 & \cdots & t_{1n}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_{i1}/d_i & \cdots & t_{ij}/d_i & \cdots & t_{in}/d_i \\ \vdots & & \vdots & & \vdots \\ t_{n1}/d_n & \cdots & t_{nj}/d_n & \cdots & t_{nn}/d_n \end{bmatrix} = \begin{bmatrix} t_{11}^{n} & \cdots & t_{1j}^{n} & \cdots & t_{1n}^{n} \\ \vdots & & \vdots & & \vdots \\ t_{i1}^{n} & \cdots & t_{ij}^{n} & \cdots & t_{in}^{n} \\ \vdots & & \vdots & & \vdots \\ t_{n1}^{n} & \cdots & t_{nj}^{n} & \cdots & t_{nn}^{n} \end{bmatrix} \tag{12}$$

Then, we adopt the normalized total influence matrix $\boldsymbol{T}_n$ from Equation (12) to normalize the columns of matrix $\boldsymbol{W}$ from Equation (8), and thereby the weighted supermatrix $\boldsymbol{W}_w$ is obtained, from Equation (13). These influence level values are the basis of normalization for determining the weighted supermatrix.

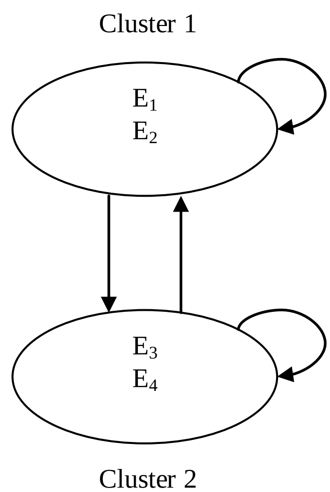

Figure 3. The simple structure graph.

$$\boldsymbol{W}_w = \begin{bmatrix} t_{11}^n \times \boldsymbol{W}_{11} & t_{21}^n \times \boldsymbol{W}_{12} & \cdots & \cdots & t_{n1}^n \times \boldsymbol{W}_{1n} \\ t_{12}^n \times \boldsymbol{W}_{21} & t_{22}^n \times \boldsymbol{W}_{22} & \vdots & & \vdots \\ \vdots & \cdots & t_{ji}^n \times \boldsymbol{W}_{ij} & \cdots & t_{ni}^n \times \boldsymbol{W}_{in} \\ \vdots & & \vdots & & \vdots \\ t_{1n}^n \times \boldsymbol{W}_{n1} & t_{2n}^n \boldsymbol{W}_{n2} & \cdots & \cdots & t_{nn}^n \times \boldsymbol{W}_{nn} \end{bmatrix} \quad (13)$$

Finally, we use Equation (10) to limit the weighted supermatrix $\boldsymbol{W}_w$ by raising it to a sufficiently large power k, until the supermatrix has converged and become a long-term stable supermatrix to obtain the global priority vectors. We demonstrate a simple example as Figure 3 to illustrate the above steps.

The unweighted supermatrix $\boldsymbol{W}$ and the total influence matrix $\boldsymbol{T}$ that are separately based on the ANP and DEMATEL approach s are stated as Equations (14) and (15).

$$\boldsymbol{W} = \begin{array}{cc} & \begin{array}{cccc} \multicolumn{2}{c}{\overline{\quad C_1 \quad}} & \multicolumn{2}{c}{\overline{\quad C_2 \quad}} \\ E_1 & E_2 & E_3 & E_4 \end{array} \\ \begin{array}{cc} C_1 & \begin{array}{c} E_1 \\ E_2 \end{array} \\ C_2 & \begin{array}{c} E_3 \\ E_4 \end{array} \end{array} & \begin{bmatrix} 1 & 0 & e_{13} & e_{14} \\ 0 & 1 & e_{24} & e_{24} \\ e_{31} & e_{32} & 1 & 0 \\ e_{41} & e_{42} & 0 & 1 \end{bmatrix} \end{array} \quad (14)$$

where $e_{ii} = 1$ denotes the effect of feedback assumed in each cluster.

In the traditional ANP procedure, it is assumed that the cluster has effect of feedback ($e_{ii} = 1$) or not ($e_{ii} = 0$) by subjective judgment. However, the total influence matrix $\boldsymbol{T}$, in Equation (15), shows that the effect of feedback really exists in each cluster $(t_{ii} \neq 0)$ to support the assumption of feedback.

$$\boldsymbol{T} = \begin{array}{cc} & \begin{array}{cc} C_1 & C_2 \end{array} \\ \begin{array}{c} C_1 \\ C_2 \end{array} & \begin{bmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{bmatrix} \end{array} \quad (15)$$

Next, by using Equations (11) and (12), we obtain a normalized matrix $\boldsymbol{T}_n$, from Equation (16).

$$\boldsymbol{T}_n = \begin{array}{cc} & \begin{array}{cc} C_1 & C_2 \end{array} \\ \begin{array}{c} C_1 \\ C_2 \end{array} & \begin{bmatrix} t_{11}/d_1 & t_{12}/d_1 \\ t_{21}/d_2 & t_{22}/d_2 \end{bmatrix} \end{array} = \begin{array}{cc} & \begin{array}{cc} C_1 & C_2 \end{array} \\ \begin{array}{c} C_1 \\ C_2 \end{array} & \begin{bmatrix} t_{11}^n & t_{12}^n \\ t_{21}^n & t_{22}^n \end{bmatrix} \end{array} \quad (16)$$

Then, we use the normalized matrix $\boldsymbol{T}_n$ in Equation (16) and the unweighted supermatrix $\boldsymbol{W}$ in Equations (14) through (13) to calculate the weighted supermatrix $\boldsymbol{W}_w$, from Equation(17).

$$\boldsymbol{W}_w = \begin{array}{cc} & \begin{array}{cccc} \multicolumn{2}{c}{\overline{\quad C_1 \quad}} & \multicolumn{2}{c}{\overline{\quad C_2 \quad}} \\ E_1 & E_2 & E_3 & E_4 \end{array} \\ \begin{array}{cc} C_1 & \begin{array}{c} E_1 \\ E_2 \end{array} \\ C_2 & \begin{array}{c} E_3 \\ E_4 \end{array} \end{array} & \begin{bmatrix} t_{11}^n & 0 & t_{21}^n e_{13} & t_{21}^n e_{14} \\ 0 & t_{11}^n & t_{21}^s e_{24} & t_{21}^s e_{24} \\ t_{12}^n e_{31} & t_{12}^n e_{32} & t_{22}^n & 0 \\ t_{12}^n e_{41} & t_{12}^n e_{42} & 0 & t_{22}^n \end{bmatrix} \end{array} \quad (17)$$

Finally, the weighted supermatrix $\boldsymbol{W}_w$ in Equation (17) is limited until it has converged and becomes a long-term stable supermatrix using Equation (10). In short, a stable limiting supermatrix can be derived by using the above steps, thereby obtaining the overall priority.

The aim of this article is to propose a feasible model that combines DEMATEL with the ANP procedure to address the problems in MDS procedure. The proposed model that we state above is able to include the weights and interrelation of all criteria, which is more suitable for real data.

AN EMPIRICAL STUDY

To compare the traditional approach and the revised approach that we propose, we separately show three kinds of results, traditional MDS, combined ANP with MDS, and combined DEMATEL with ANP to modify MDS.

This empirical study examines the similarities of seven

Table 1. The traditional MDS proximity matrix.

	A	B	C	D	E	F	G
A	0	2.25	1.75	2.25	5.25	3.75	3.75
B	2.25	0	2.25	3	3	2	5
C	1.75	2.25	0	3.75	2.5	4.75	3
D	2.25	3	3.75	0	2.5	4	3.25
E	5.25	3	2.5	2.5	0	2.5	4
F	3.75	2	4.75	4	2.5	0	2.75
G	3.75	5	3	3.25	4	2.75	0

Table 2. The coordinates of two-dimensional configuration.

Objects	Dimension 1	Dimension2
A	1.38	-0.28
B	0.47	1.38
C	0.94	0.15
D	0.32	-1.13
E	-1.74	0.29
F	-0.49	1.10
G	-0.88	-1.50

e-shopping stores using MDS analysis. As we know, each store may adopt a different marketing strategy to attract the most consumers in a competitive market, so the similarities of stores that consumers use are very important for marketing agencies. Because the effect of marketing strategy may obscure the consumer's perception of the utility of a given store, we can capture the configuration from the subjective perception of a consumer for each store (if any two stores use the same low price marketing strategy, consumers will perceive that they may have the similar property for the price criterion) (Alam, 2009; Alam and Khalifa, 2009). It is very important for stores to understand the differential configuration of competitors, because they can adopt the most effective strategy to hold the market share. From the final analysis of our technique, the evaluator can identify the dissimilarities between competitive stores in the market, and the analysis results are notably different from the traditional MDS analysis.

In this case, we adopt four criteria of vendor-specify quality and service quality for e-shopping stores to be evaluated, including the perceived price saving, reputation (these two are derived from vendor-specific quality), reliability, and responsiveness (these two are derived from service quality) that are based on DeLone and McLean's IS success model (DeLone and McLean, 2003) for measuring the relative success of e-shopping stores.

The proximity matrices of the four criteria are shown in Appendix A. In order to compare the traditional MDS with the combined approach that we propose, we first treat the weights and interrelation of all criteria as equal and

Table 3. The weighted MDS proximity matrix based on ANP.

	A	B	C	D	E	F	G
A	0	2.18	1.82	2.32	5.35	3.73	3.62
B	2.18	0	2.29	2.97	3.14	1.94	5.06
C	1.82	2.29	0	3.62	2.56	4.68	2.91
D	2.32	2.97	3.62	0	2.41	4.15	3.21
E	5.35	3.14	2.56	2.41	0	2.56	3.94
F	3.73	1.94	4.68	4.15	2.56	0	2.76
G	3.62	5.06	2.91	3.21	3.94	2.76	0

independent to calculate the proximity matrix based on Tables A.1-A.4 in Appendix A. The result is shown in Table 1. In the proximity matrix, we can use the traditional MDS procedure to obtain the coordinates of two dimensional configurations to show the similarities structure of stores in Table 2 and Figure 4.

From Figure 4, we can initially conclude that there are six segments in this market by using the traditional MDS analysis. Stores A and C have similar marketing positions, but the others are part of several specific small numerous markets.

Next, we consider the effects of the weights in the MDS analysis by adding the ANP approach alone. Because the evaluation criteria should have the effects of interdependence and feedback during the evaluation process, we assume the network relationship shown in Figure 5.

First, we judge the relative relationships between the criteria from the standpoint of a single criterion obtained from the knowledge or opinion of experts to form a pair-wise comparison initial unweighted supermatrix *W* (Appendix B), shown in Equation(19). Next, the weighted supermatrix (normalized matrix) is derived by transforming each column to sum exactly to unity (1.00), as in Equation (18). Then, each element in a column is divided by the number of clusters, as in Equation (20). Finally, we obtain the final weighted supermatrix by limiting the power *k*, as in Equation (10), to form Equation (21). By using Equations (21) and (22), we obtain the final weighted proximity matrix, shown in Table 3.

$$\boldsymbol{C} = \begin{array}{c} \\ C_1 \\ C_2 \end{array} \begin{array}{c} \begin{array}{cc} C_1 & C_2 \end{array} \\ \begin{bmatrix} 1/2 & 1/2 \\ 1/2 & 1/2 \end{bmatrix} \end{array} \quad (18)$$

$$\boldsymbol{W} = \begin{array}{cc} & \\ & \\ C_1 & \begin{array}{c} E_1 \\ E_2 \end{array} \\ C_2 & \begin{array}{c} E_3 \\ E_4 \end{array} \end{array} \begin{array}{c} \begin{array}{cccc} \multicolumn{2}{c}{C_1} & \multicolumn{2}{c}{C_2} \\ E_1 & E_2 & E_3 & E_4 \end{array} \\ \begin{bmatrix} 1 & 0 & 0.40 & 0.60 \\ 0 & 1 & 0.60 & 0.40 \\ 0.40 & 0.30 & 1 & 0 \\ 0.60 & 0.70 & 0 & 1 \end{bmatrix} \end{array} \quad (19)$$

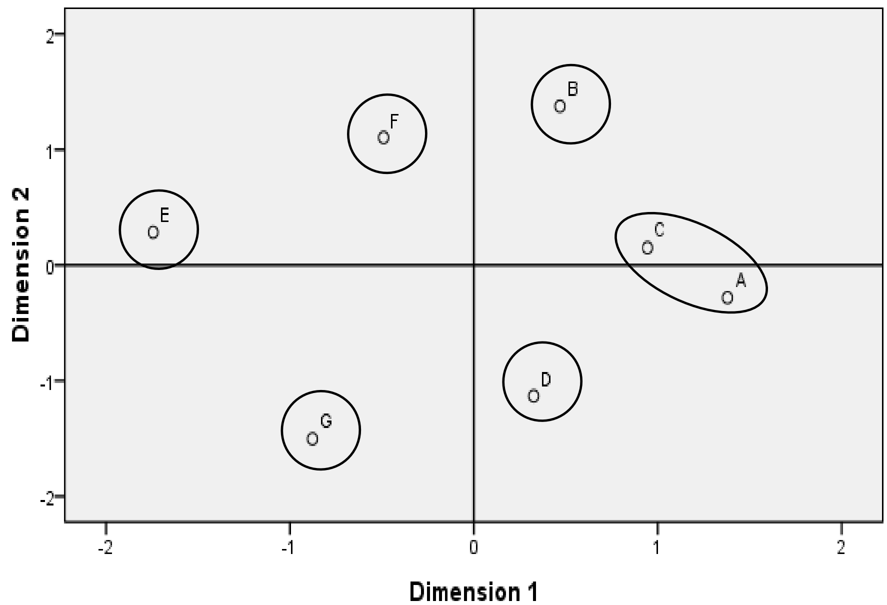

Figure 4. Two-dimensional relationship mapping.

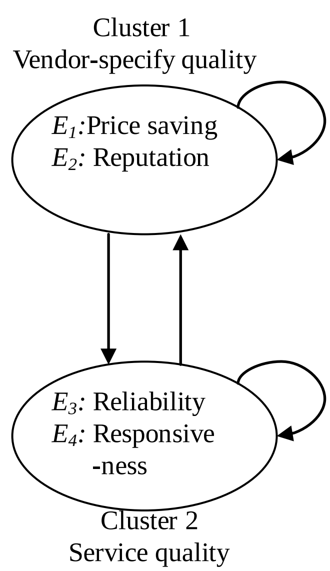

Figure 5. The structure of elements.

$$
W_w = \begin{array}{cc|cccc} & & C_1 & & C_2 & \\ & & E_1 & E_2 & E_3 & E_4 \\ C_1 & E_1 & 1/2 & 0 & 0.4/2 & 0.6/2 \\ & E_2 & 0 & 1/2 & 0.6/2 & 0.4/2 \\ C_2 & E_3 & 0.4/2 & 0.3/2 & 1 & 0 \\ & E_4 & 0.6/2 & 0.7/2 & 0 & 1 \end{array} \tag{20}
$$

$$
W_f = \lim_{k \to \infty} W_w^k = \begin{array}{cc|cccc} & & C_1 & & C_2 & \\ & & E_1 & E_2 & E_3 & E_4 \\ C_1 & E_1 & 0.26 & 0.26 & 0.26 & 0.26 \\ & E_2 & 0.24 & 0.24 & 0.24 & 0.24 \\ C_2 & E_3 & 0.18 & 0.18 & 0.18 & 0.18 \\ & E_4 & 0.32 & 0.32 & 0.32 & 0.32 \end{array} \tag{21}
$$

Then, $\boldsymbol{w} = (w_1, ..., w_e, ..., w_4) = (0.26, 0.24, 0.18, 0.32)$ by using Equation (21) and

$$
\boldsymbol{S}^* = \sum_{e=1}^{4} w_e \boldsymbol{S}_e,
$$

$$
\boldsymbol{S}^* = \left[s_{ij}^* \right], \quad i, \quad j \in \{1, 2, ..., 7\} \tag{22}
$$

where $\boldsymbol{S}^*$ denotes the integrated weighted proximity matrix that is used in MDS analysis. w_e denotes the weight of *e*-th criterion, and $\boldsymbol{S}_e$ denotes the proximity matrix according to the *e*-th criterion. The weighted proximity matrix of the seven e-shopping stores is represented in Table 3.

Then, we can obtain two-dimensional configurations in Table 4 and Figure 6.

To compare Figure 4, although there are some changes between the relative locations shown in Figure 6, this result remains similar to the traditional MDS analysis and does not account for the varied influence between objects.

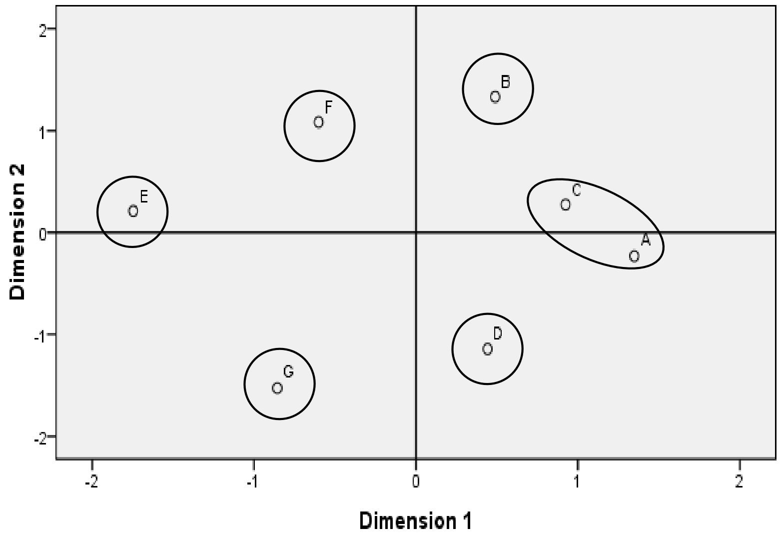

Figure 6. Two-dimensional relationship mapping.

Table 4. The Coordinates of two-dimensional configuration.

Objects	Dimension 1	Dimension2
A	1.35	-0.23
B	0.49	1.33
C	0.92	0.27
D	0.44	-1.14
E	-1.75	0.21
F	-0.60	1.08
G	-0.86	-1.53

Therefore, we adopt DEMATEL approach to detect the complex relationships and build an impact-relation map (IRM) of clusters. Furthermore, we obtain the influence levels of all clusters over the others. Then, we adopt these influence level values as the basis of the normalized supermatrix for determining the degrees of influence between clusters to obtain a revised weighted super-matrix.

First, using the steps of DEMATEL discussed earlier, we can obtain the normalized total influence matrix $\boldsymbol{T_n}$, shown in Equation (23).

$$\boldsymbol{T}_n = \begin{array}{c} \\ C_1 \\ C_2 \end{array} \begin{array}{c} \begin{array}{cc} C_1 & C_2 \end{array} \\ \begin{bmatrix} 0.2 & 0.8 \\ 0.5 & 0.5 \end{bmatrix} \end{array} \tag{23}$$

Next, we adopt the normalized total influence matrix T_n and the unweighted supermatrix $\boldsymbol{W}$ in Equation (19) by Equation (13) to calculate the new weighted supermatrix, shown in Equation (24). Then, we obtain the final weighted supermatrix by limiting the power k, as in Equation (10), to form Equation (25).

$$\boldsymbol{W}_w = \boldsymbol{T}_n \boldsymbol{W} = \begin{array}{cc} & \\ & \\ C_1 & \begin{array}{c} E_1 \\ E_2 \end{array} \\ C_2 & \begin{array}{c} E_3 \\ E_4 \end{array} \end{array} \begin{array}{c} \overbrace{\quad E_1 \quad E_2 \quad}^{C_1} \overbrace{\quad E_3 \quad E_4 \quad}^{C_2} \\ \begin{bmatrix} 0.2 & 0 & 0.2 & 0.3 \\ 0 & 0.2 & 0.3 & 0.2 \\ 0.32 & 0.24 & 0.5 & 0 \\ 0.48 & 0.56 & 0 & 0.5 \end{bmatrix} \end{array} \tag{24}$$

$$\boldsymbol{W}_f = \lim_{k \to \infty} \boldsymbol{W}_w^k = \begin{array}{cc} & \\ & \\ C_1 & \begin{array}{c} E_1 \\ E_2 \end{array} \\ C_2 & \begin{array}{c} E_3 \\ E_4 \end{array} \end{array} \begin{array}{c} \overbrace{\quad E_1 \quad E_2 \quad}^{C_1} \overbrace{\quad E_3 \quad E_4 \quad}^{C_2} \\ \begin{bmatrix} 0.20 & 0.20 & 0.20 & 0.20 \\ 0.18 & 0.18 & 0.18 & 0.18 \\ 0.22 & 0.22 & 0.22 & 0.22 \\ 0.40 & 0.40 & 0.40 & 0.40 \end{bmatrix} \end{array} \tag{25}$$

Through using Equations (22) and (25), we also obtain the final weighted proximity matrix by considering the network relations of the criteria to form Table 5. Finally, we obtain two-dimensional configurations as shown in Table 6 and Figure 7.

The results of this analysis show that there are only four segments in this market, which more accurately represents the market configuration, and the results are notably different from the traditional MDS analysis.

DISCUSSION

MDS analysis is a useful tool for representing the

Table 5. The weighted proximity matrix based on the combined method.

	A	B	C	D	E	F	G
A	0	2.22	2.01	2.17	5.65	3.65	3.87
B	2.22	0	2.38	2.83	3.18	1.81	5.43
C	2.01	2.38	0	3.87	2.81	5.06	3.01
D	2.17	2.83	3.87	0	2.40	4.41	3.01
E	5.65	3.18	2.81	2.40	0	2.58	4.04
F	3.65	1.81	5.06	4.41	2.58	0	2.82
G	3.87	5.43	3.01	3.01	4.04	2.82	0

Table 6. The Coordinates of two-dimensional configuration.

Objects	Dimension 1	Dimension2
A	-0.18	1.49
B	1.46	0.31
C	0.12	1.41
D	-0.99	-0.27
E	0.22	-1.63
F	1.05	-0.61
G	-1.67	-0.43

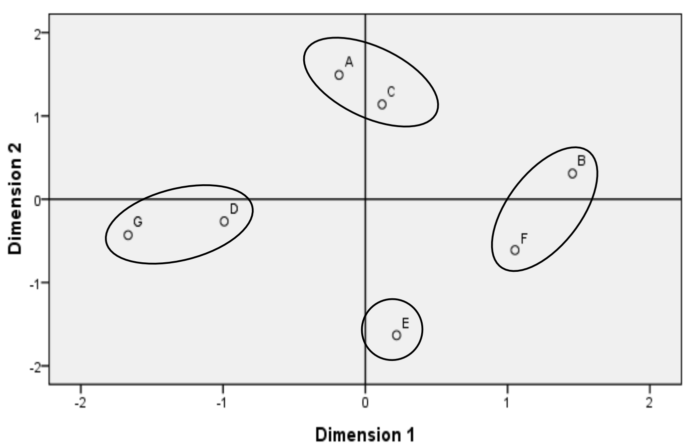

Figure 7. Two-dimensional relationship mapping.

structure of relationships between objects. However, in the traditional MDS procedure, we usually ignore the unequal weights and interrelation of criteria in forming the proximity matrices. This may imply similarities of e-shopping stores when there is none because of the false assumed weighting used in MDS. In our empirical study, we represent the difference between the traditional MDS and the combined approach that we propose.

The empirical study is to identify the similarities between the seven e-shopping stores, and the proximity matrices are based on four criteria: price saving, reputation, reliability, responsiveness. In the traditional MDS procedure, the interrelation and weights of criteria are treated as independent and equal, which is not realistic. By combining DEMATEL with ANP to modify the MDS procedure, we obtained a result that is closer to the real data.

Although there is a temptation and tendency among empirical researchers to re-use established models based on relationship marketing, the technology acceptance model, and the theory of planned behavior, without due consideration of the underlying nature and context of similarities of e-shopping stores, we suggest that such a “one size fits all” approach to modeling online purchase behavior may provide a less than adequate understanding of purchase behaviors. This study demonstrates that our proposed approach is so unique that traditional models of purchase behavior have not addressed it. The proposed approach in this study can be increasingly important with the increasing scope and role of the internet and other information technology systems in our lives as an important means of electronic commerce and online purchase. To accurately attack the target market, a manager of e-shopping store should learn about how to identify the similarities of e-shopping stores with other competitors in the market by conducting periodical market surveys. By doing so, managers can keep producing valuable feedbacks about how e-shopping stores can fit well with their marketing strategy from consumer perception for characteristic of e-shopping stores.

Another good feature of this combined approach is that it can help us to know the relations and magnitudes among clusters according to the result of DEMATEL. It can provide additional useful information for decision makers. Therefore, the combined approach that we propose can provide more information and make the results more suitable for real situations.

Conclusions

In a complex system, it is difficult for human to judge the similarities between objects, however we can divide the whole systems into subsystems to make it easier by using the ANP approach. In practice, these subsystems are always related by interdependence and feedback. This article proposes an approach that combines DEMATEL with ANP to deal with the complexity caused by this interdependence. From our final results, we can conclude that the hybrid model that we propose can provide more information for a decision maker by obtaining a precise snapshot of objects in MDS analysis. To further improve upon the traditional MDS technique, a non-linear additive hybrid model that can be used for constructing the proximity matrix will be addressed in our future work.

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Appendix A

Table A1. The proximity matrix on the price saving criterion.

	A	B	C	D	E	F	G
A	0	2	1	3	5	6	3
B	2	0	1	5	3	3	3
C	1	1	0	3	1	3	2
D	3	5	3	0	2	3	5
E	5	3	1	2	0	2	4
F	6	3	3	3	2	0	3
G	3	3	2	5	4	3	0

Table A2. The proximity matrix on the reputation criterion.

	A	B	C	D	E	F	G
A	0	2	1	3	3	2	2
B	2	0	3	2	3	2	4
C	1	3	0	2	2	3	3
D	3	2	2	0	3	3	3
E	3	3	2	3	0	3	3
F	2	2	3	3	3	0	2
G	2	4	3	3	3	2	0

Table A3. The proximity matrix on the reliability criterion.

	A	B	C	D	E	F	G
A	0	3	2	1	6	4	6
B	3	0	2	3	2	2	6
C	2	2	0	6	3	7	4
D	1	3	6	0	3	4	3
E	6	2	3	3	0	2	5
F	4	2	7	4	2	0	3
G	6	6	4	3	5	3	0

Table A4. The proximity matrix on the responsiveness criterion.

	A	B	C	D	E	F	G
A	0	2	3	2	7	3	4
B	2	0	3	2	4	1	7
C	3	3	0	4	4	6	3
D	2	2	4	0	2	6	2
E	7	4	4	2	0	3	4
F	3	1	6	6	3	0	3
G	4	7	3	2	4	3	0

Appendix B

Table B1. The pairwise comparison of the criteria in ANP.

Criterion	*X*	How much *X* is more important than *Y* with respect to criterion?	*Y*
Price	Reliability	2/3	Responsiveness
Reputation	Reliability	3/7	Responsiveness
Reliability	Price	2/3	Reputation
Responsiveness	Price	3/2	Reputation