A Brand Position Model for the Resort Hotels at Kenting Area in Taiwan

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Abstract: - *Under the considerations for the rapid development in leisure tourism and the demand increase for resort hotels, most enterprises will meet a pressure of drastic competition. Therefore, they will intend to build a unique brand in the mind of consumers and to enhance competitiveness and increase their profits. In this study, we will address the issue on the position of brand equity and key factors of competition for the resort hotels. The questionnaire method will be applied to collect the data and the resort hotels in Kenting area will be taken as an illustrative example in our study. The primary findings of this study can be summarized as follows:*

1. *Customers will have a higher degree of recognition for the environmental quality, local quality and uniqueness brand to the resort Hotels in Kernting area.*
2. *According to the brand equity diagram derived by using the multi-dimensional scaling (MDS) to those tourists at kernting area, we can find out that those resort hotels can be clustered into four clusters.*
3. *The brand equity model can be constructed well via using the conventional discriminant analysis and the backpropagation neural network technique. And, the full model and the reduced model can be also constructed after screening the important factors.*

From above findings, it can provide the useful reference about the marketing strategy and differentiation competition for the resort hotels in Kenting area. It will aid the competition analysis since the enterprise would like to realize their position on the competition environment via the brand equity cognitions.

Key-Words: Brand Equity, Resort Hotels, competition analysis, leisure tourism, Backpropagation neural networks (BPNN)

1. Introduction

The market requirements of leisure tourism had gradually increased and the relating products also had rapidly diversified along with the huge changes for the tourism market. Obviously, the resort hotels played an important role during the tourism industries. After screening out the entire environment at Taiwan, the physical products derived from the restore hotels can easily copied by the other hotels and it will lead to a higher homogeneity among those hotels. Hence, most hotels will be hard to directly obtain their competence advantage via the physical products. Restated, the invisible products will become an important factor when the customers making their decisions about travel accommodation. Besides, due to the policy change for Taiwanese government, the restore hotels will meet a new tourism market with the larger competitive pressures. Hence, how to mine their core competence will become an important issue to most restore hotels. Aaker (1991) had mentioned that the brand equity can keep the competence and retain the profit for most enterprises. However, the products derived by hotels can not apply for the patent due to the higher homogeneity among them. Hence, the hotel's brand will have an important affection when the customers making their buying decision. Besides, reviewing the historical studies about brand, most of them frequently focused on the physical products and consumer goods. The issue about the brand equity of tourism industry had seldom been mentioned. That is, the brand equity, positioning and the competitive factors will became our primary focus. According to the viewpoint about the background and motivation, we will intend to make the study about the significant difference for those characteristics of brand equity, e.g organizational association, awareness, uniqueness brand, location quality, environment quality, equipment quality, service quality and loyalty (Blasckston, 1992; Lassar et al., 1995; Keller, 1998; Shen & Hsieh, 2006; Konecnik & Gartner, 2007; Kim et al., 2008). Then, we can inference the competitive factors and the awareness positioning according to the difference of brand equity. An example, owing the restore hotels at Kenting area in Taiwan, will be applied to demonstrate the rationality of this study. The obtained results can provide more useful information about modifying the marketing strategy, keeping the competitive advantages, creating the customer's equity and enhancing the customer's loyalty.

2. Background Introduction

2.1. Brand Equity

When the brand equity had been mentioned from 1980, it became an important concept during the market development. However, the standard definition of brand equity can not be made yet. Aaker (1991) and Biel (1992) mentioned that the brand equity is a name, a norm, a label, a signal, a design or an integrated index to recognize the product/service of enterprises. Brand equity can make to increase or decrease the extra profits of product/service defined in customers' mind. Keller (1993) also mentioned that the purpose of brand equity is to improve the marketing productivity. That is, it addresses how to increase the efficiency of marketing budget and how to make a better strategy about the target market and product position via analyzing the customers' behaviors.

2.2. Position Strategy

Aaker & Shansby (1982) mentioned that the position strategy of brand is a key factor about forming the customers' recognition and decision-making. That is, all elements among the marketing plan will affect the result of brand position. Hence, in their study, six position strategies were proposed: attribute position, price/quality position, application position, ending user position, product category position and competitors' position. Then, Kotler et al. (1996) and Kotler (1999) also proposed the benefit to be the seventh position. Ries & Trout (1981) pointed out three strategies can be used: the first one is to mine a new and non-overlap segmentation with the enough ending consumers from market; the second is to modify and enhance the position in the ending consumer's mind; the third is to find out the weakness of competitors and hit it to reduce the position in the ending consumers' mind. Dolrymple & Parson (1986) viewed the position as the combination of the product diversity and market segmentation. Not only the druthers of consumers need to be evaluated, but the feature of product/service also need to be changed according to it.

2.3. Characteristics of Brand Equity

Blasckston (1992) viewed the brand equity as two categories: the first one is the basic equity, which denotes the related marketing variables including the price, package, channels, brand; the other is the added value equity, which denotes the invisible features. According to the contents mentioned from the Aaker's book, the primary contents of the brand equity will include the brand loyalty, brand awareness and brand association. Then, Keller (1998) pointed out that the brand characteristics based on the consumers will consist of the brand awareness, which including the brand recognition and brand recall, and the brand accommodation, which including the brand association, druthers and uniqueness. Lassar et al. (1995) construct a brand equity measure model consisting of five elements (product representation, social image, recognition degree, reliability, attribution) and find out a positive relationship between the ranks of the brand equity and price level. Brand awareness and loyalty also be addressed based on the customer-based brand equity by Konecnik & Gartner (2007). Furthermore, Kim et al. (2008) also point out five factors that influence the creation of brand equity through successful customer relationships as trust, customer satisfaction, relationship commitment, brand loyalty, and brand awareness.

2.4. Multicharacteristical scaling technique (MDS)

Multidimensional Scaling (MDS) describes a family of techniques for the analysis of proximity data on a set of stimuli to reveal the hidden structure underlying the data. The proximity data can come from similarity judgments, identification confusion matrices, grouping data, same-different errors or any other measure of pair wise similarity. The main assumption in MDS is that stimuli can be described by values along a set of characteristics that places these stimuli as points in a multidimensional space and that the similarity between stimuli is inversely related to the distances of the corresponding points in the multidimensional space. The Minkowski distance metric provides a general way to specify distance in a multidimensional space:

$$d_{ij} = \left[\sum_{k=1}^{n} \left| x_{ik} - x_{jk} \right|^{r} \right]^{1/r} \quad (1)$$

where n is the number of characteristics, and x_{ik} is the value of characteristic k for stimulus i. With r =2, the metric equals the Euclidian distance metric while r=1 leads to the city-block metric.

A Euclidian metric is appropriate when the stimuli are composed of integral or perceptually fused characteristics such as the characteristics of brightness and saturation for colours. The city-block metric is appropriate when the stimuli are composed of separable characteristics such as size and brightness (Attneave, 1950). In practice, the Euclidian distance metric is often used because of mathematical convenience in MDS procedures. MDS can be applied with different purposes. One is exploratory data analysis; by placing objects as points in a low dimensional space, the observed complexity in the original data matrix can often be reduced while reserving the essential information in the data. By a representation of the pattern of proximities in two or three characteristics, researchers can visually study the structure in the data.

It also has been used to discover the mental representation of stimuli that explains how similarity judgments are generated. Sometimes, MDS reveals the psychological characteristics hidden in the data that can meaningfully describe the data. The multidimensional representations resulting from MDS are also often useful as the representational basis for various mathematical models of categorization, identification, and/or recognition memory (Nosofsky, 1992) or generalization (Shepard, 1987). There are many different MDS techniques to analyze proximity data and many issues in the analysis and interpretation of the results. First, there is the distinction between metric and non-metric MDS. The goal of metric MDS is to find a configuration of points in some multidimensional space such that the inter-point distances are related to the experimentally obtained similarities by some transformation function (e.g., a linear transformation function). If the proximity data are generated with Euclidian distances for some stimulus configuration, then a procedure called classical metric MDS (Torgeson, 1965) can exactly recreate the configuration of points. Because a closed form solution exists to find such a configuration of points, classical metric MDS can be performed efficiently on large matrices. In non-metric MDS (first devised by Shepard in 1962), the goal is to establish a monotonic relationship between inter-point distances and obtained similarities. The advantage of non-metric MDS is that no assumptions need to be made about the underlying transformation function; the only assumption is that the data is measured at the ordinal level. Kruskal (1964) proposed a measure for the deviation from monotonicity between the distances d_{ij} and the observed dissimilarities o_{ij} called the stress function:

$$S = \sqrt{\frac{\sum_{ij} \left(d_{ij} - d^{*}_{ij} \right)^{2}}{\sum_{ij} d_{ij}^{\,2}}} \quad (2)$$

Note that the observed dissimilarities o ij do not appear in this formula. Instead, the discrepancy between the predicted distances d ij and the target distances d ij are measured. Based on the current configuration of points, the target distances d ij are found by monotonic regression and represent the distances that are monotonically related to the observed dissimilarities o ij . Several iterative minimization algorithms exist to move the object points in a multidimensional space in order to minimize stress (see Borg & Groenen, 1997). In the face similarity example, Figure 1d displays what is known as the Shepard plot. It shows the relationship between predicted distances d_{ij} and observed dissimilarities as filled circles and can serve to understand what metric transformation would be appropriate to relate one to the other. The line in the plot shows the relationship between the target distances d_{ij} found by monotonic regression and observed dissimilarities. Kruskal stress essentially is a measure based on the sum of the squared deviations between the filled circles and the line along the abscissa. MDS is said to be metrical if it based on measured proximities and non-metrical when the proximities are based on judgment (Jobson, 1992). The original method of MDS was metric (Torgerson, 1958). In current paper the analysis is based on non-metrical data and therefore the non-metric MDS is used. The data is analyzed by the statistical software package SPSS and the ALSCAL algorithm created by Takane et al. (1977). The detailed content can be referred to Jobson (1992) and Torgerson (1958).

2.5. Discriminant Analysis

Discriminant Analysis may be used for two objectives: either we want to assess the adequacy of classification, given the group memberships of the objects under study; or we wish to assign objects to one of a number of (known) groups of objects. In both cases, some group assignments must be known before carrying out the Discriminant Analysis. Such group assignments, or labelling, may be arrived at in any way. Hence Discriminant Analysis can be employed as a useful complement to Cluster Analysis (in order to judge the results of the latter) or Principal Components Analysis (Davis, 1986; Weslowsky, 1976). Linear Discriminant Analysis is the 2-group case of MDA. It optimally separates two groups, using the Mahalanobis metric or generalized distance. It also gives the same linear separating decision surface as Bayesian maximum likelihood discrimination in the case of equal class covariance matrices. There is no best discrimination method. A few remarks concerning the advantages and disadvantages of the methods studied are as follows. Analytical simplicity or computational reasons may lead to initial consideration of linear discriminant analysis. Linear discrimination is the most widely used in practice (Shen & Hsieh, 2006; Zhang & Ruan, 2007). Often the 2-group method is used repeatedly for the analysis of pairs of multigroup data (yielding k(k-1)/2 decision surfaces for k groups). To estimate the parameters required in quadratic discrimination more computation and data is required than in the case of linear discrimination. If there is not a great difference in the group covariance matrices, then the latter will perform as well as quadratic discrimination. LDA had been applied in positioning, product management, and marketing research. In marketing, discriminant analysis is often used to determine the factors which distinguish different types of customers and/or products on the basis of surveys or other forms of collected data. The use of discriminant analysis in marketing is usually described by the following steps: Formulate the problem and gather data - Identify the salient attributes consumers use to evaluate products in this category - Use quantitative marketing research techniques (such as surveys) to collect data from a sample of potential customers concerning their ratings of all the product attributes. The data collection stage is usually done by marketing research professionals. Survey questions ask the respondent to rate a product from one to five (or 1 to 7, or 1 to 10) on a range of attributes chosen by the researcher. Anywhere from five to twenty attributes are chosen. They could include things like: ease of use, weight, accuracy, durability, colourfulness, price, or size. The attributes chosen will vary depending on the product being studied. The same question is asked about all the products in the study.

Estimate the Discriminant Function Coefficients and determine the statistical significance and validity - Choose the appropriate discriminant analysis method. The direct method involves estimating the discriminant function so that all the predictors are assessed simultaneously. The stepwise method enters the predictors sequentially. The two-group method should be used when the dependent variable has two categories or states. The multiple discriminant method is used when the dependent variable has three or more categorical states. Use Wilks's Lambda to test for significance in SPSS or F stat in SAS. The most common method used to test validity is to split the sample into an estimation or analysis sample, and a validation or holdout sample. The estimation sample is used in constructing the discriminant function. The validation sample is used to construct a classification matrix which contains the number of correctly classified and incorrectly classified cases. The percentage of correctly classified cases is called the hit ratio. The detailed content about Discriminant Analysis can be referred to Davis (1986) and Weslowsky (1976).

2.6. Backpropagation Artificial Neural Networks (BPNN)

Among the several conventional supervised learning neural models including the perceptron, backpropagation neural network (BPNN), learning vector quantization (LVQ), and counter propagation network (CPN), the BPNN model is frequently used (Neural Ware, 1990; Hsieh, 2001; Hsieh, 2006; Varela et al., 2006; Buscema et al., 2006; Cheng et al., 2007;Hsieh & Lu, 2007) and, therefore, it will be selected herein. A BPNN consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. Detailed descriptions of the algorithm can be found in various sources (Neural Ware, 1990; Rumelhart et al., 1986). To develop a backpropagation neural network, the training and testing data set are firstly collected. The data sets consist of both the input parameters and the resulting output parameters. The backpropagation learning algorithm employs a gradient- or steepest- heuristic that enables a network to self organize in ways that improve its performance over time. The network first uses the input data set to produces its own output. This forward pass through the backpropagation network begins as the input layer receive the input data pattern and passes it to the hidden layer. Each processing element (PE) calculates an activation function in first summing the weighted inputs. This sun is then used by an activation function in each node to determine the activity level of the processing node. The output generated by the network is compared to the known target value. If there is no difference, no learning takes place. If a difference exists, the resulting error term is propagated back through the network, using a gradient- or steepest- descent heuristic to minimize the error term by adjusting the connection weights.

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$$\Delta W_{kj} = \eta \delta_k O_j$$

where

ΔW_{kj}=the change to be made in the weight from the j-th to k-th unit following the presentation of an input pattern,

δ_k=the error signal for unit k after the presentation of an input pattern,

O_j=the j-th element of the output pattern produced by the presentation of an input pattern,

η=the learning rate that governs how fast the network will encode a set of input/output patterns.

The backpropagation rule for changing weights following the presentation of an input/output pair for the hidden layer j is

$$\Delta W_{ji} = \eta \delta_j O_i$$

where

ΔW_{ji}= the change to be made in the weight from the j-th to i-th unit following the presentation of an input pattern,

δ_j=the error signal for unit j after the presentation of an input pattern,

O_i=the i-th element of the output pattern produced by the presentation of an input pattern,

η=the learning rate that governs how fast the network will encode a set of input/output patterns.

As for the training phase, a signal input pattern is presented and the network adjusts the set of weights in all the connecting links such that the desired output is obtained at the output node. On accomplishing the adjustment, the next pair of input and output target value is presented and the network learns that association. The architecture diagram for BPNN will be graphically depicted in Figure 1.

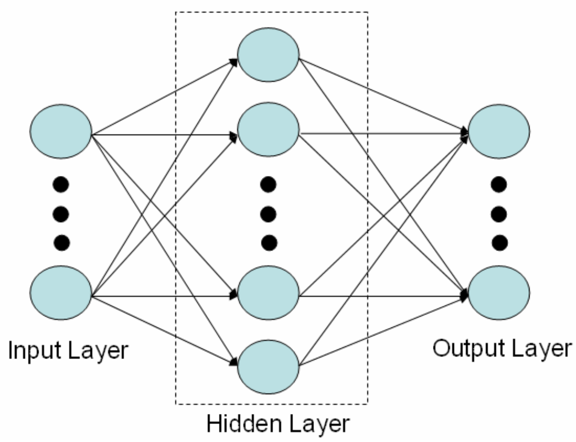

Figure 1. The architecture diagram for BPNN.

3. Methods

3.1. Questionnaire

The questionnaire we used was developed from the literature review and the purpose of this study. This questionnaire will consist of three parts. And the first part is the eight characteristics of brand equity including the organizational association, awareness, uniqueness, location quality, environment quality, amusement- equipment quality, service quality and loyalty. The second part was designed to gather information relating to overall satisfaction. All items of measures were rated on 5-point Likert –type scale, ranging from 1 (extreme disagreement) to 5 (extreme agreement). The final part dealt with the demographic backgrounds of the respondents.

3.2. Sampling

Such as hotel lobby, parking lot and bus stop of those hotels in Kenting area were the place we chose to gather information. Convenience sampling was adopted in this study. The survey was carried out over one month period from December 2005 to January 2006. Among 160 questionnaires distributed in those place and a total of 130 usable questionnaires for this study were obtained (response rate: 81.25%).

3.3. Data Analysis

In this study, the collected data were analyzed by using descriptive statistics including frequencies and means to show the mean rating of various characteristics of brand equity and each item of measures from the views of travelers in Kenting area so as to fathom the difference in factors that travelers valued. Reliability analysis was applied to assess the internal consistency of the variables retained in each item. Cronbach's α was also used to test the reliability of each question. Generally, three levels of Cronbach's α were set up as the over 0.7, between 0.35 and 0.7, and under 0.35 level. It must be appreciably higher relativity and reliability in over 0.7 level, and in between 0.35 and 0.7 must be acceptable. And then it must be rejected in 0.35. Further, one-way ANOVA was adopted to test whether the various characteristics (organizational association, combination awareness, uniqueness, location, environment quality, amusement- equipment quality, service quality and loyalty) differed significantly. Finally, multidimensional scaling was adopted and a perceptual map was developed to show the position of brand equity and the key factors of competition among hotels in Kenting area. Besides, the discriminant function and artificial neural networks techniques were also applied to constructing the brand equity model. It can aid the enterprises to hold the position information during the competitive environment.

4. The analysis of brand equity

4.1. Summary result

The summary information about the observed travelers will be given in Table 1. The ratio of female is larger than the ratio of male (62.31%>37.69%), the age distribution will be centralized in 20-30, the student will be the primary customer cluster, the more education degree can be found as the university, the primary income structure will be corresponding to NT. 5001-15000, and the most travelers will live in the south part.

Table 1. The summary data about the travelers.

Item	Category	Count	Ratio	Item	Category	Count	Ratio
sexy	Male	49	37.69%	Education	Junior high school	0	0.00%
	Female	81	62.31%		Senior high school	10	7.69%
age	Under 20	11	8.46%		College	17	13.08%
	21-30	87	66.92%		University	83	63.85%
	31-40	22	16.92%		Graduate school	20	15.38%
	41-50	7	5.38%	income	Under NT. 5000	24	18.46%
	Above 51	3	2.31%		NT. 5001-15000	52	40.00%
Occupation	Student	69	53.08%		NT. 15001-25000	24	18.46%
	Self-Employed	10	7.69%		NT. 25001-35000	14	10.77%
	Business	6	4.62%		NT. 35001-45000	5	3.85%
	House-keeping	3	2.31%		NT. 45001-55000	3	2.31%
	Political servant	8	6.15%		Above NT. 55000	8	6.15%
	Service industry	20	15.38%	location	North part	22	16.92%
	agriculture, fishing & herd	0	0.00%		Middle part	31	23.85%
	Else	14	10.77%		South part	68	52.31%
					East part	9	6.92%
					off-shore island	0	0.00%

The previous studies had pointed out that the validity degree should be actually measured by the measurement scale. All constructed items of the questionnaire in this study referred to relevant references or theories, and then the level of validity can be verified. As for the reliability of this study, Cronbach’s values were adopted and they were showed in Tables 2. Each of the reliability of characteristic was over 0.66 other than service quality, hence, the reliability of the questionnaire used in this study also can be verified.

Table 2. The reliability α values for the eight characteristics.

Characteristics	Cronbach's α
Organizational Association	0.71
Brand Awareness	0.66
Brand Uniqueness	0.79
Location Quality	0.74
Environment Quality	0.80
Equipment Quality	0.83
Service Quality	0.50
Loyalty	0.89

And then, the mean scores of the eight characteristics were also listed in Table 3. After reviewing such results, environment quality, location quality and brand uniqueness will have the larger evaluation score. On the contrary, the awareness is the lowest.

Table 3. The mean score of the eight characteristics.

Characteristics	Mean	Characteristics	Mean
Organizational Association	3.82	Environment Quality	3.98
Brand Awareness	3.66	Equipment Quality	3.77
Brand Uniqueness	3.88	Service Quality	3.70
Location Quality	3.91	Loyalty	3.79

4.2. Cognition analysis for brand equity

The perceptual map of Muticharacteristical Scaling for the hotels in Kenting (Figure 2) shows that hotels can be divided into four similar competitive clusters by the coordinate location. The first group includes Caesar Park Hotel-Kenting (Caesar) and Howard Beach, Kending (Howard). Yoho Beach Club & SPA (Yoho) and Chateau Beach, Kending (Chateau) were in the second group. The third group will include OX Hill Hotel (OX), Swanlake Resort Hotel SPA (Swanlake) and Ken-Ting Toong Mao Kao-Shang –Ching Hotel (Kao-Shang –Ching). The final group included ChinaTrust Hotel (ChinaTrust) and Sea Biew loge Hotel (Sea Biew loge).

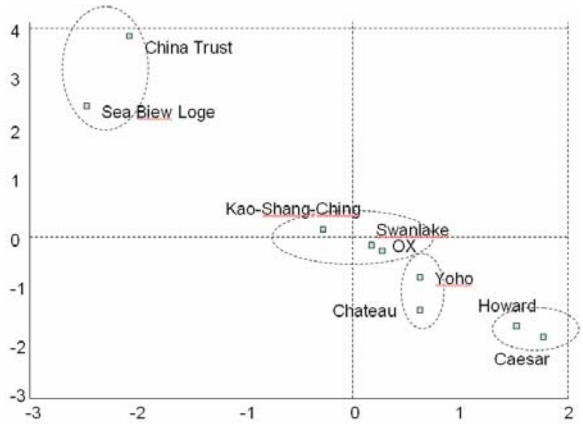

Figure 2. The perceptual map of hotel position.

Next, ANOVA analysis will be applied to each characteristic in order to analyze the significant characteristics with respect to the brand equity. From the result listed in Table 4, the organizational association, brand uniqueness, location quality, environment quality and equipment quality denote the significant affections on brand equity with the diversity of hotels (α =0.05).

Table 4. The summary results of ANOVA.

Characteristics	F value	P value
Organizational Association	2.449	0.014*
Brand Awareness	1.664	0.105
Brand Uniqueness	3.867	0.000*
Location Quality	2.694	0.007*
Environment Quality	2.080	0.036*
Equipment Quality	2.634	0.008*
Service Quality	1.664	0.105
Loyalty	1.730	0.089

Table 5 will denote the mean score of those eight characteristics for those nine hotels in Kentung area. Figure 3 shows that Caesar is superior to Howard on many characteristics such as awareness, location quality, environment quality and loyalty, but the characteristics such as organizational association, uniqueness brand, equipment quality and service quality of Howard are superior to Caesar. As for the groups B appeared in Figure 4 shows that the Yoho is superior to Chateau on the characteristics such as organizational association, uniqueness, service quality and loyalty. And the awareness, location quality, environment quality and equipment quality of Chateau are superior to Yoho. Figure 5 presents that service quality of OX in the group C is the best than others. Kao-Shang –Ching is superior to others on the characteristics of location quality, environment quality and equipment quality. The characteristics such as organizational association, combination awareness, uniqueness for Swanlakem are superior to others. Figure 6 shows that ChinaTrust is superior to Sea Biew loge on awareness environment quality service quality and loyalty. As for the organizational association, uniqueness, location quality, equipment quality, Sea Biew loge is superior to ChinaTrust. Broadly speaking, the key competitive factors for resort hotels of four clusters are as following. As for the first group, the key competitive factors for Caesar are awareness and location quality. The competitive advantages of Howard are equipment quality. For the second group, the location quality is the key competitive factor for Chateau and the service quality is for Yoho. In the third group, the key competitive factors of OX are service quality and equipment quality. The organizational association, awareness, and loyalty are the advantages for Swanlake. For the final group, the organizational association, location quality and equipment quality of Sea Biew loge are the key competitive factors. The awareness, service quality and loyalty are the competitive advantages of ChinaTrust.

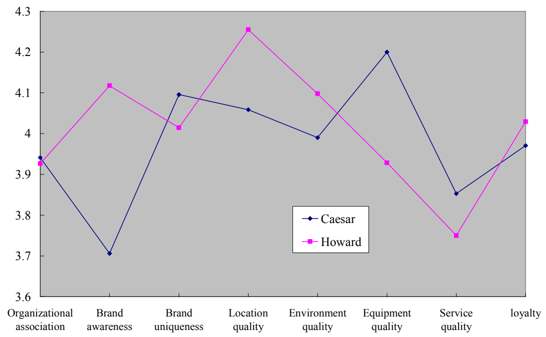

Figure 3. Comparison diagram of Cluster 1.

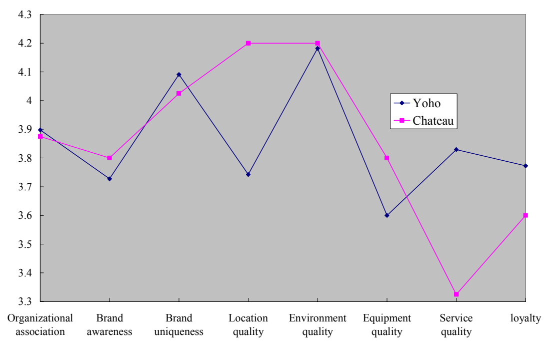

Figure 4. Comparison diagram of Cluster 2.

Table 5. The mean score of eight characteristics for each hotel.

Characteristics / Hotels	Organizational association	Brand awareness	Brand uniqueness	Location quality
Caesar	3.9412	3.7059	4.0956	4.0588
Howard	3.9265	4.1176	4.0147	4.2549
Sea Biew Loge	3.5	2.5	3.25	3.5
Yoho	3.8977	3.7273	4.0909	3.7424
Chateau	3.8750	3.8	4.025	4.2
OX	3.75	3.3929	3.6964	3.8571
China Trust	3.1	3.3	3.05	3.13333
Kao-Shanf-Ching	3.6	3.5	3.5	3.9333
Swanlake	3.9	3.6	3.85	3.7333

Characteristics / Hotels	Environment quality	Equipment quality	Service quality	loyalty
Caesar	3.9902	4.2	3.8529	3.9706
Howard	4.0980	3.9286	3.75	4.0294
Sea Biew Loge	3.1667	3.3333	3.0	2.75
Yoho	4.1818	3.6	3.8295	3.7727
Chateau	4.2	3.8	3.325	3.6
OX	3.9286	3.7321	4.0357	3.9643
China Trust	3.333	3.0	3.4	3.0
Kao-Shanf-Ching	3.9902	3.8	3.4	3.2
Swanlake	3.8667	3.55	3.4	4.0

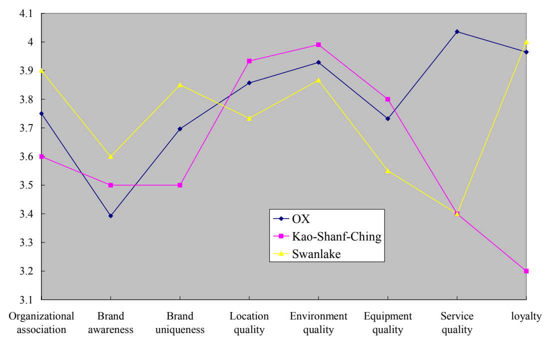

Figure 5. Comparison diagram of Cluster 3.

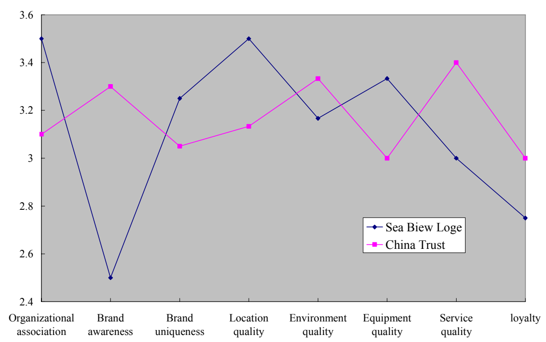

Figure 6. Comparison diagram of Cluster 4.

4.3. The brand equity model

In this section, we will apply the Discriminant function (Model 1) and artificial neural networks (Model 2) into constructing the brand equity model. The detailed content about the model construction and the analysis results will be given as follows:

4.3.1 Model 1

Next, we will use the collected data to construct the brand equity recognition model. Discriminant function technique will be applied into achieving model construction. Herein, we consider the twenty-eight measured items as the independent variables. Four clusters will be the classification to be used in this model construction. After performing the discriminant analysis in SPSS 12.0, we can get the function of discriminant analysis and the first function will be given as follows:

Fisher discriminant function (1): $23.52+2.648 * \text{evaluation}_{\text{(quality abilities of administration and management)}} + 1.287 * \text{evaluation}_{\text{(great resource of creation)}} + \cdots + 0.648 * \text{evaluation}_{\text{(be willing to choose the same hotel next time)}}$

Such result was obtained under the statistic test condition in Table 6.

Table 6. The result of Fisher's discriminant function.

Discriminant function	eigenvalue	Variation(%)	Accumulated variation	Wilk's Lambda	Chi-square	Significance
1	0.516	64.1	64.1	0.5	83.1	0.000
2	0.123	15.2	79.4	0.76	33.1	0.242
	...					

We randomly select about thirty records to be the test set. Next, the thirty data were inputted into the constructed Fisher's discriminant function and the classification rate can be computed in Table 7.

Table 7. The classification rate for the test set.

		I	II	III	IV	Category
Original category	Number	5	10	8	7	Count
I	5	5	0	0	0	The classification rate is computed as 25/30=83.33%
II	11	0	9	2	0	
III	8	0	1	6	1	
IV	6	0	0	1	5	

4.4.2 Model 2

Next, we will use the same collected data to construct the brand equity model by using BPNN technique. As for the model construction via BPNN, the relating parameters of BPNN will be primarily determined. The relating parameters about BPNN model will be chosen as: learning rate (0.15~0.25), momentum (0.85~0.9), delta learning rule, learning epochs (5000). After pilot running about model construction, we get the suitable parameter settings to be as learning rate (0.2), momentum (0.852), delta learning rule, learning epochs (5000). Herein, we need to decide the optimum network architecture of BPNN, i.e. the number of PEs in input-hidden-output layer. According to the recommendation from relating literatures (Neural Ware, 1990; Hsieh, 2001; Hsieh, 2006), the initial PEs in the hidden layer can be computed as (the number of PEs in input layer + the number of PEs in output layer)/2; the ratio about testing/training samples can be chosen as about 1/4. That is, the number of PEs in the input and the output layer will be set as 26 (the measured items) and 4 (the number of clusters). Besides, we randomly keep about thirty records to be the validation set. And, seventy-five records were randomly selected as the training samples from the reminder 100 records, i.e. the testing/training ratio will be arrived at 1/4. After performing the necessary BPNN analysis, we compare the root mean square of error (RMSE) values for the training and testing sets and the optimum architecture can be determined. Figure 7 graphically depicts the comparison diagram about the RMSE values. From this figure, 26-18-4 will be chosen as the optimum BPNN architecture. In order to verify the effectiveness of the chosen architecture, we input the thirty records (the validation set) into the constructed BPNN. Herein, twenty six records denote the correct classification. The classification rate can be computed as 86.67% (i.e. 26/30). Such constructed model will aid the managers to obtain the prediction information from the measured items and it also provided the useful information about their necessary recommendations about the future improvement activities.

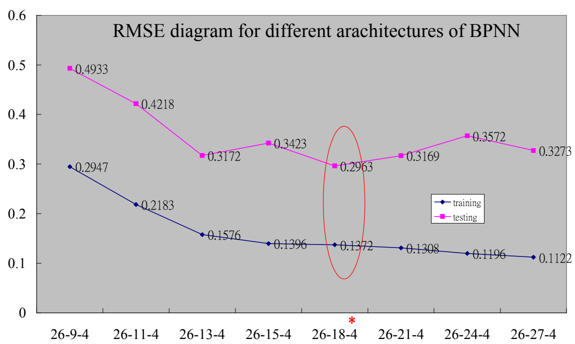

Figure 7. The RMSE diagram of BPNN-full model.

Besides, we also constructed a reduced model by taking the evaluation of the organizational association, awareness, uniqueness brand, location quality, environment quality, equipment quality, service quality, loyalty as the input signals of BPNN. And, the number of cluster was also viewed as the output signal of BPNN. Then, we will perform the construction procedure via try and error. After the model construction, we got 8-12-4 architecture of BPNN to be an optimum choice. Such result can be referred to Figure 8. In order to verify the effectiveness of the chosen reduced model, we also input the thirty records (the validation set) into the constructed BPNN. Herein, twenty eight records denote the correct classification. The classification rate can be computed as 93.33% (i.e. 28/30). Such constructed reduced model will aid the managers to obtain the prediction information from the measured items and it also provided the useful information about their necessary recommendations about the future improvement activities.

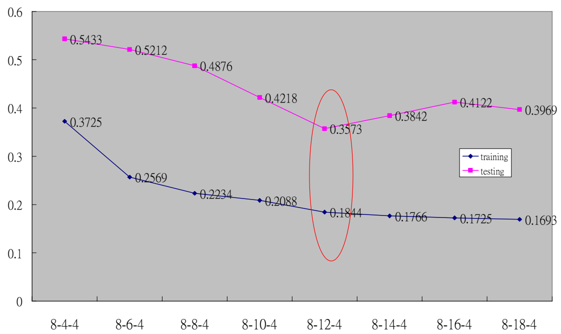

Figure 8. The RMSE diagram of BPNN-reduced model.

5. Concluding Remarks

After performing the data analysis for addressing the issue of brand equity, we can obtain the useful information like as the customers will have a higher degree of recognition for the environmental quality, local quality and uniqueness brand to the resort Hotels in Kernting area; the similar competitive clusters and their whole competitive situation of resort hotels in Kenting area can be discovered via using MDS technique. Besides, we also proposed a model construction approach to address the brand equity model by using the discriminant analysis and the BPNN technique. From those results, the brand equity can be viewed as resource of profits and a powerful weapon for most restore hotels to the competitive environment. Hence, the managers of those hotels at Kernting area should realize the position of brand in the ending consumer's mind and then the competitive advantages can be created depending on our obtained results. Restated, the brand can be viewed as a useful marketing tool to create the consumer's value and enhance the consumer's loyalty.

References

[1] Aaker, D. A. (1991). Managing Brand Equity. NY: The Free Press.

[2] Aaker, D .A. and Shansby J. G. (1982). Positioning Your Product. Business Horizons. 25(3), 56-62.

[3] Blackstone, M. (1992). Observations: Building Brand Equity by Managing the Brand's Relationships. Journal of Advertising Research, 78-83.

[4] Biel, A. L. (1992). How Brand Image Drives Brand Equity. Journal of Advertising Research, 32(11), 6-12.

[5] Borg, I., & Groenen, P. (1997). Modern Multicharacteristical Scaling, Theory and Applications. New York, Springer-Verlag.

[6] Buscema, M., Terzi, S., Breda, M., (2006). Using Sinusoidal Modulated Weights Improve Feed-Forward Neural Network Performances in Classification and Functional Approximation Problems. WSEAS Transactions on Information Science and Applications, 3(5), 885-893.

[7]Cheng, S. H., Hsieh, K. L., Tong, L. I., (2007). Benefit Prediction Model by Employing BPNN from the Viewpoint of Organization. WSEAS Transactions on Information Science and Applications, 4(3), pp.516-522.

[8] Dolrymple, D. J. & Parson, L J. (1986). Marketing Management Strategy and Cases. NY: John Wiley and Sons, Inc.

[9] Fisher, R. A. (1936). The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenics, 7, pp.179-188.

[10]Hsieh, K. L. and Tong, L. I. (2001). Applying artificial neural networks to optimize the multiple quality responses mixing qualitative and quantitative characteristic. Computers in Industry, 46(1), 1-12.

[11]Hsieh, K. L. (2006). Parameter Optimization of a Multi-response Process for Lead frame Manufacturing by Employing Artificial Neural Networks. International Journal of Advanced Manufacturing Technology, 28(5-6), 584-59.

[12]Hsieh, K. L. & Lu, Y. S., (2007). Constructing Yield Model of TFT-LCD Manufacturing Process by using ANNs. WSEAS Transaction on Systems, 6(4), pp.887-893.

[13]Kim, K. H., Kim, K. S., Kim, D. Y.,; Kim, J. H.,; Kang, S. H. (2008). Brand equity in hospital marketing. Journal of Business Research, 61(1), 75-82.

[14]Keller, K. L. (1993). Conceptualizing Measuring, and Managing Customer Based Brand Equity. Journal of Marketing Research, 1-22.

[15]Keller, K. L. (1998). Strategic brand management: building, measuring, and managing brand equity. New Jersey: Prentice Hall.

[16]Konecnik, M. & Gartner, W. C. (2007). Customer-based brand equity for a destination. Annals of Tourism Research, 34 (2), 400-421.

[17]Kotler, P., Ang, S. H., Leong, S. M. & Tan, C. T. (1996). Marketing Management: An Asian Perspective. Singapore: Prentice Hall.

[18]Kolter, P. (1999). Kolter on marketing：How to create, win, and dominate markets. New Jersey：The Free Press.

[19]Kruskal, J.B. (1964). Multicharacteristical scaling by optimizing goodness of fit to a nonmetric hypothesis. Psychometrika, 29, 1-27, 115-129.

[20]Lassar, W., Mittal, B. & Sharma, A. (1995). Measuring Customer-Based Brand Equity. Journal of Consumer Marketing, 12(4), 11-19.

[21]NeuralWare, Inc., (1990). NeuralWorks Professional II/Plus and NeuralWorks Exporer, Penn Center West: NeuralWare, Inc.

[22]Nosofsky, R.M. (1992). Similarity scaling and cognitive process models. Annual Review of Psychology, 43, 25-53.

[23]Ries, A. & Trout, J. (1981). The Positioning Era Cometh. Advertising Age, May, 236-249.

[24]Rumelhart, D. E., Hinton, G. E. and Williams, R. J., (1986). Learning internal representations by error propagation, Parallel Distributed Processing: Explorations in the Microstructure of cognition, Edited by Rumelhart, D. E., McClelland, J. L., MIT Press, Cambridge, MA, 318-362.

[25]Shen, C. C. & Hsieh, K. L., (2006). Discriminant Model for Customer Lifetime Value via BPNN Modelling. WSEAS Transaction on Business and Economics, 3(7), pp.511-516.

[26] Shen, C. C. & Hsieh, K.-L., (2006). Incorporating Fuzzy Aggregation Operator and Grey Relationship Analysis into Constructing a MCDM Model. WSEAS Transactions on Information Science and Applications, 4(5), 2100-2106.

[27]Shepard, R. N. (1962). Analysis of proximities: Multicharacteristical scaling with an unknown distance function I & II. Psychometrika, 27, 125-140, 219-246.

[28]Shepard, R.N. (1987). Towards a universal law of generalization for psychological. Science, 237, 1317:1323.

[29]Torgeson, W.S. (1965). Multicharacteristical scaling of similarity. Psychometrika, 30, 379-393.

[30]Varela, A., Moreno, H. G., Lopez, C. P., (2006). Prediction of the Effect of Premium Changes on Companies Insurance Customer Rates Using Neural Networks. WSEAS Transactions on Information Science and Applications, 3(4), 846-851.

[31]Zhang, C. & Ruan, Q., (2007). Face Recognition Using Wavelet based Complete Linear Discriminant Analysis and Fuzzy Integral. WSEAS Transactions on Information Science and Applications, 4(8), 1333-1340.