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Intelligent Decision Support for New Product Development: A Consumer-Oriented Approach

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Abstract: This paper presents a consumer-oriented design approach to determine the optimal form design of characteristic toys that best matches consumers' preferences. The consumer-oriented design approach is based on the process of Kansei Engineering using neural networks (NNs) and the technique for order preference by similarity to ideal solution (TOPSIS). The NN model is used to build a design decision support database, and then an NN-based TOPSIS decision support model is used to enable product designers to obtain the optimal design alternatives that best meet consumers' preferences for a new characteristic toy design.

Keywords: New Product Development; Kansei Engineering; TOPSIS; Neural Networks; Decision Making

1 Introduction

The 21st century is a consumer-centered century, while the 20th century is called a machine-centered century. It is an essential issue that how to design highly-reputable and hot-selling products in the current competitive market [5,6,7]. The key factor that influences the success of a new product is capturing the "voice of consumers". Consequently, product designers need to comprehend consumers' preferences in order to design successful products [3,4].

Nowadays, there is an interesting social phenomenon in eastern Asia, particularly in Taiwan, Japan, and Hong Kong. Many companies produce various kinds of characteristic toys (dolls, mascots, cuddly toys, or called "gongzi" in Mandarin) in order to get consumers' attention and enhance the amount of sales (as shown in Fig. 1). According to the marketing surveys or reports [7], the characteristic toys can affect companies sales up by 10% to 30%. This outcome is fantastic for companies and product designers, particularly in a competitive market.

Fig. 1: An example of characteristic toys sold at the chain convenience store in Taiwan.

In order to help product designers work out the optimal combination of product design elements for matching consumers' preferences, a consumer-oriented approach, called Kansei Engineering [8,9], is used to build a design decision support model. Kansei Engineering is an ergonomic methodology and a design strategy for affective design to meet consumers' preferences [6]. The word Kansei indicates consumers' psychological requirements or emotional feelings of a product. Kansei Engineering has been applied successfully in the product design field to explore the relationship between consumers' preferences and product forms [4,5,6,7]. To illustrate how the consumer-oriented

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approach works, we conduct an experimental study on characteristic toys for their great popularity in eastern Asia.

In subsequent sections, we first present the methodology proposed in this study, including the neural networks (NNs) due to its powerful learning and prediction abilities [10], and the technique for order preference by similarity to ideal solution (TOPSIS) due to its wide use in multiattribute decision making (MADM) [12]. Then an experimental study on characteristic toys is conducted to show how Kansei Engineering can be used to extract representative samples and form elements as numerical data sets required for analysis. Finally, an NN-based TOPSIS decision support model is built to help product designers get the optimal alternatives (ideal solutions) that best meet consumers' preferences for the new product design.

2 Methodology

In this section, the concept of NNs and TOPSIS implemented in this study are introduced.

2.1 Neural Networks (NNs)

NNs are non-linear models and are widely used to examine the complex relationship between input variables and output variables. Due to the effective learning ability, the NNs have been applied successfully in a wide range of fields, using various learning algorithms [10]. The NNs are well suited to formulate the product design process for matching product forms (the input variables) to consumers' preferences (the output variables), which is often a black box and cannot be precisely described [4]. In this paper, we use the multilayered feedforward neural networks trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm [10].

A typical three-layer network consists of an input layer, an output layer, and one hidden layer, with n, m, and p neurons respectively (indexed by i, j, and k respectively) [10]. The w_{ij} and w_{jk} represent the weights for the connection between input neuron i $(i = 1,2,\cdots,n)$ and hidden neuron j $(j = 1,2,\cdots,m)$, and between hidden neuron j $(j = 1,2,\cdots,m)$ and output neuron k $(k = 1,2,\cdots,p)$ respectively. In training the network, a set of input patterns or signals, $(X1,X2,,Xn)$ is presented to the network input layer. The network then propagates the inputs from layer to layer until the outputs are generated by the output layer. This involves the generation of the outputs (y_j) of the neurons in the hidden layer as given in (1) and the outputs (y_k) of the neurons in the output layer as given in (2).

$$y_i = f\left(\sum_{i=1}^{n} x_i w_{ij} - \theta_j\right) \tag{1}$$

$$y_k = f\left(\sum_{j=1}^{m} x_j w_{jk} - \theta_k\right) \tag{2}$$

where $f(.)$ is the sigmoid activation function as given in (3), and θ_j and θ_k are threshold values.

$$f(x) = \frac{1}{1+e^{-X}} \tag{3}$$

If the outputs (y_k) generated by (2) are different from the target outputs (y_k^*), errors $(e_1,e_2,\cdots,e_p)$ are calculated by (4) and then propagated backwards from the output layer to the input layer in order to update the weights for reducing the errors.

$$e_k = y_k^* - y_k \tag{4}$$

The weights (w_{jk}) at the output neurons are updated as $w_{jk} + \Delta w_{jk}$, where Δw_{jk} is computed by (known as the delta rule)

$$\Delta w_{jk} = \alpha y_i \delta_k \tag{5}$$

where α is the learning rate (usually $0 < \alpha \leq 1$) and δ_k is the error gradient at neuron k, given as

$$\delta_k = y_k(1 - y_k)e_k \tag{6}$$

The weights (w_{ij}) at the hidden neurons are updated as $w_{ij} + \Delta w_{ij}$, where Δw_{ij} is calculated by

$$\Delta w_{ij} = \alpha x_i \delta_j \tag{7}$$

where α is the learning rate (usually $0 < \alpha \leq 1$) and δ_j is the error gradient at neuron j, given as

$$\delta_j = y_j(1 - y_j)\sum_{k=1}^{p} \delta_k w_{jk} \tag{8}$$

The training process is repeated until a specified error criterion is satisfied.

2.2 The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Based on the concept of the degree of optimality, the overall preference value of an alternative is determined by its distance to the positive ideal solution and to the negative ideal solution. This concept has been implemented by a widely used MADM method called the technique for order preference by similarity to ideal solution (TOPSIS) [1,2,11,12]. The advantages of using this concept have been highlighted by (a)its intuitively appealing logic, (b)its simplicity and comprehensibility, (c)its computational efficiency, (d)its ability to measure the relative performance of the alternatives with respect to individual or all evaluation criteria in a simple mathematical form, and (e)its applicability in solving various MADM problems [12].

The main procedure of the TOPSIS is given as follows [11]:

Step 1: Obtain the decision matrix C for m criteria (e.g. product design elements or consumers' preferences) and n alternatives (e.g. the number of product samples or combinations), given as

$$C = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1m} \\ C_{21} & C_{22} & \cdots & C_{2m} \\ \vdots & \vdots & C_{ij} & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nm} \end{bmatrix} \tag{9}$$

where C_{ij} represent the performance rating values of alternative A_i $(i = 1,2,\cdots,n)$ with respect to criterion B_j $(j = 1,2,\cdots,m)$.

Step 2: Normalize the decision matrix C to allow a comparable scale for all criteria by

$$r_{ij} = \frac{C_{ij}}{\sqrt{\sum_{i=1}^{n} C_{ij}^2}}, i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{10}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & r_{ij} & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{11}$$

Step 3: Calculate the weighted normalized decision matrix. The weighted normalized value of v_{ij} can be calculated by

$$v_{ij} = w_j \times r_{ij}, \sum_{j=1}^{m} w_j = 1 \tag{12}$$

$$V = \begin{bmatrix} w_1r_{11} & w_2r_{12} & \cdots & w_mr_{1m} \\ w_1r_{21} & w_2r_{22} & \cdots & w_mr_{2m} \\ \vdots & \vdots & w_jr_{ij} & \vdots \\ w_1r_{n1} & w_2r_{n2} & \cdots & w_mr_{nm} \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1m} \\ v_{21} & v_{22} & \cdots & v_{2m} \\ \vdots & \vdots & v_{ij} & \vdots \\ v_{n1} & v_{n2} & \cdots & v_{nm} \end{bmatrix} \tag{13}$$

where w_j is the normalized weight of the j^{th} criterion.

Step 4: Determine the positive and negative ideal solutions or alternatives. The positive ideal alternative is a hypothetical alternative in which all criterion values correspond to the best level. On the contrary, the negative ideal alternative is also a hypothetical alternative in which all criterion values correspond to the worst level. The positive ideal alternative A^+ and the negative ideal alternative A^- are given as

$$\begin{aligned} A^+ &= \left\{v_1^+, v_2^+, \cdots, v_m^+\right\}, \\ A^- &= \left\{v_1^-, v_2^-, \cdots, v_m^-\right\} \end{aligned} \tag{14}$$

where

$$\begin{aligned} v_j^+ &= \max\left(v_{1j}, v_{2j}, \cdots, v_{nj}\right), \\ v_j^- &= \min\left(v_{1j}, v_{2j}, \cdots, v_{nj}\right), j = 1,2,\cdots,m. \end{aligned} \tag{15}$$

Step 5: Calculate the separation measures. The separation (distance) between alternatives can be measured by the n-dimensional Euclidean distance. The positive ideal alternative S_i^+ is given as

$$S_i^+ = sqrt \sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2, i = 1,2,\cdots,n \tag{16}$$

Similarly, the negative ideal alternative S_i^- is given as

$$S_i^- = sqrt \sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2, i = 1,2,\cdots,n \tag{17}$$

Step 6: Obtain an overall preference value (relative closeness) for each alternative A_i, relative to other alternatives, by

$$P_i = \frac{S_i^-}{(S_i^+ + S_i^-)}, i = 1,2,\cdots,n \tag{18}$$

The larger the preference value, the more preferred the alternative.

Step 7: Rank the design alternatives by their P_i value.

3 A Consumer-Oriented Experiment

In this section, we present the primary procedure of Kansei Engineering in the context of characteristic toys, including how to extract the representative experimental sample, how to conduct the morphological analysis of product form elements, and how to assess the preferences of consumers.

3.1 Extracting Representative Experimental Samples

In the experimental study, we investigate and categorize various characteristic toys with local and aboriginal cultures in Taiwan. We first collect about 179 characteristic toys and then classify them based on their similarity degree by a focus group that is formed by 6 product experts/designers with at least two years experience of product design. In order to avoid cognitive overhead or reduce the cognitive demand from the experimental subjects (mentioned in Section 3.3) and to maintain the judgment consistency, the reduction of experimental samples is necessary. The focus group eliminates some highly similar samples through discussions. Then the hierarchy cluster analysis is used to extract representative samples of characteristic toys. The 35 representative characteristic toy samples are selected by the cluster tree diagram (please refer to [7] for details), including 28 samples as the training set and 7 samples as the test set for building the NN model.

3.2 Conducting Morphological Analysis of Product Form Elements

The product form is defined as the collection of design features that consumers will appreciate. The morphological analysis, concerning the arrangement of objects and how they conform to create a whole of Gestalt, is used to explore all possible solutions in a complicated problem regarding a product form [6].

The morphological analysis is used to extract the product form elements of the 35 representative characteristic toy samples. The 6 product experts/designers of the focus group are asked to decompose the representative samples into several dominant form elements and form types according to their knowledge and experience. Table 1 shows the result of the morphological analysis, with 7 product form elements and 24 associated product form types being identified. The form type indicates the relationship between the outline elements. For example, the ”width ratio of head and body (X_2)” form element has 3 form types, including ”headbody (X_{21})”, ”head=body (X_{22})”, and ”head body (X_{23})”. A number of design alternatives can be generated by various combinations of morphological elements.

3.3 Assessing Consumers’ Preferences

The emotional assessment experiment is usually performed to elicit consumers’ psychological feelings or preferences about a product using the semantic differential method. Image words are often used to describe consumers’ preferences of the product in terms of ergonomic and psychological estimation [8]. With the identification of the form elements of the product, the relationship between consumers’ preferences and product forms can be established.

In this study, we collect about 110 image words which are used to describe the characteristic toys (e.g. vivid, attractive, traditional, etc.) from magazines, product catalogs, designers, artists, and toy collectors. Then we apply factor analysis and cluster analysis according to the result of semantic differential method. Finally, 3 representative image words, i.e. ”cute (CU)”, ”artistic (AR)”, and ”attractive (AT)”, are determined (please refer to [7] for details). To obtain the assessed values for the emotional preferences of 35 representative characteristic toy samples, a 100-point scale (1-100) of the semantic differential method is used. 150 subjects (70 males and 80 females with ages ranging from 15 to 50) are asked to assess the form (look) of characteristic toy samples on an image word scale of 0 to 100, for example, where 100 is most attractive on the AT scale.

The last 3 columns of Table 2 show the 3 assessed values of the 35 samples, including 28 samples in the training set and 7 samples in the test set (asterisked). For each selected characteristic toy in Table 2, the first column shows the characteristic toy number and Columns 2-8 show the corresponding type number for each of its 7 product form elements, as given in Table 1.

Table 2 provides a numerical data source for building neural network model, which can be used to develop a design decision support model for the new product design and development of characteristic toys.

4 An NN-based TOPSIS Decision Support Model

The analysis of the NN model and the TOPSIS decision support model are presented in this section.

4.1 Analysis of the NN Model

To examine how a particular combination of product form element matches the CU, AR, and AT preferences, we use the most widely used rule, the number of input neurons + the number of output neurons/2, for determining the number of neurons in the single hidden layer [10].

The 7 product form elements in Table 1 are used as the 7 input variables for the NN model. If the characteristic toy has a particular product form type, the value of the corresponding input neuron is 1, 2, 3, 4 or 5. The assessed average values of the CU, AR, and AT preferences are used as the output neurons. Consequently, the number of neurons in the input layer is 7, the number of hidden neurons is 5, and the number of output neurons is 3, respectively.

In many neural network studies, there are various analyses using different learning rates and momentum factors for getting the better structure of the NN model. In this study, we use a learning rate of 0.05 and a momentum of 0.5 due to the complexity and noise of the data (please refer to [7] for details). The learning rule used is Delta-Rule and the transfer function is Sigmoid for all

Table 1: The morphological analysis of characteristic toys.

Form Elements	**Form Types**				
	Type 1	**Type 2**	**Type 3**	**Type 4**	**Type 5**
Length ratio of head and body(X_1)	≥ 1.1	1:1 1:2	$<$ 1:2		
Width ratio of head and body (X_2)	head $>$ body	head = body	head $<$ body		
Costume style (X_3)	one-piece	two-pieces	robe		
Costume pattern (X_4)	simple	striped	geometric	mixed	
Headdress (X_5)	tribal	ordinary	flowered	feathered	arc-shaped
Appearance of facial features (X_6)	eyes only	partial features	entire features		
Overall appearance (X_7)	cute style	semi-personified style	personified style		

layers. All of input and output variables (neurons) are normalized before training [4]. The experimental samples are separated into two groups: 28 training samples and 7 test samples. The training process of the model is not stopped until the cumulative training epochs are over 25,000. The root of mean square error (RMSE) of the model is 0.0481 (smaller than 0.05). The result indicates that the structure of the NN model is promising for predicting the output variables (i.e. the CU, AR, and AT preferences).

To evaluate the performance of the NN model in terms of its predictive ability, the 7 samples in the test set are used. Rows 2-4 of Table 3 show the average assessed values of the CU, AR, and AT preferences on the 7 test samples given by the 150 subjects, and Rows 5-7 show the predicted values for the 3 preferences by using the NN model trained in the previous section. The last column of Table 3 shows the RMSE of the NN model for the test set.

As indicated in Table 3, the RMSE of the NN model is 0.0931. This result suggests that the NN model has a high predictive consistency (an accuracy rate of 91.69%, 100%-9.31%) for predicting the values of the CU, AR, and AT preferences of characteristic toys. This demonstrates that the NN model is suitable for modeling consumers' preferences on product images of characteristic toys.

4.2 The TOPSIS Decision Support

The NN model enables us to build a design decision support database that can be used to help determine the optimal product form for best matching specific consumers' preferences. The design decision support database can be generated by inputting each of all possible combinations of form types on each form element to the NN model individually for generating the associated preferences values. The resultant design decision support database for characteristic toys consists of 4,860 ($= 3 \times 3 \times 3 \times 4 \times 5 \times 3 \times 3$) different combinations of product form elements, together with their associated CU, AR, and AT preference values. In other words, there are 4,860 design alternatives generated by the NN model.

The TOPSIS method is used to determine the optimal alternatives (ideal solutions), if the specific design requirement or concept is proposed by consumers or product designers. For example, if consumers prefer a new characteristic toy with "extremely cute", "slightly artistic", and "moderately attractive", the TOPSIS design decision support can be expressed in the following steps [1,11]:

Step 1: Obtain the decision matrix C, i.e. the CU, AR, and AT values of 4,860 design alternatives generated by the NN model.

Step 2: Normalize the CU, AR, and AT values to allow a comparable scale for all criteria by (10).

Step 3: Calculate the weighted normalized decision matrix. The weighted normalized value can be calculated by (12). As an illustration, we can assign the value of 1, 3, and 5 for the "slightly", "moderately", and "extremely", respectively. Hence, the normalized weights of the "extremely cute", "slightly artistic", and "moderately attractive" are $5/(5+1+3)$, $1/(5+1+3)$, and $3/(5+1+3)$, respectively.

Step 4: Determine the positive and negative ideal alternatives. Obtain the positive ideal alternative A^+ and the negative ideal alternative A^- by (14) and (15). In the illustration, we have $A^+ = (1.0503, 0.1211, 0.3903)$, and $A^- = (0.0104, 0.0006, 0.0011)$, respectively.

Step 5: Calculate the separation measures. The positive ideal alternative S_i^+ is calculated by (16) and the negative ideal alternative S_i^- is calculated by (17).

Table 2: The assessment of consumers' preferences.

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	CU	AR	AT
1	3	2	1	1	4	3	3	73	61	64
2	1	1	1	1	1	2	3	72	45	43
3	2	2	1	3	3	1	1	70	64	41
4*	***2***	***3***	***2***	***4***	***2***	***2***	***2***	***63***	***52***	***54***
5	2	2	1	1	4	2	1	68	59	55
6	2	2	2	4	3	2	2	65	66	69
7*	***2***	***2***	***2***	***4***	***5***	***2***	***2***	***52***	***66***	***61***
8	2	3	2	4	4	2	2	53	61	60
9	2	2	3	2	2	2	2	63	59	59
10	2	2	1	3	2	2	2	55	63	65
11	1	1	2	3	4	2	1	70	69	67
12	1	1	3	2	2	2	1	57	54	61
13	3	3	2	4	4	3	3	48	69	76
14	3	3	1	4	4	3	3	62	68	78
15	3	3	2	2	2	3	3	54	63	68
16*	***3***	***3***	***1***	***2***	***3***	***3***	***3***	***62***	***74***	***72***
17	3	3	2	4	2	3	3	55	68	66
18	2	3	3	2	2	2	2	71	65	61
19	2	2	1	1	2	3	3	41	52	75
20	2	2	2	1	1	3	3	39	53	63
21*	***2***	***2***	***2***	***2***	***3***	***3***	***3***	***41***	***50***	***58***
22	2	2	2	3	2	3	2	44	74	62
23	2	2	2	1	2	3	3	43	59	74
24	2	2	1	3	2	3	1	54	60	62
25	2	2	2	2	2	1	1	63	52	62
26*	***1***	***2***	***2***	***2***	***4***	***3***	***2***	***58***	***71***	***68***
27	1	2	1	2	4	3	2	57	61	66
28	1	1	2	2	1	1	1	62	56	73
29	1	1	1	3	5	3	2	76	67	74
30*	***1***	***1***	***1***	***3***	***3***	***3***	***2***	***68***	***59***	***65***
31	1	1	3	2	2	3	2	71	60	70
32*	***1***	***1***	***1***	***4***	***4***	***1***	***1***	***61***	***49***	***51***
33	1	1	1	4	5	1	1	72	59	57
34	2	3	2	4	2	2	2	38	48	49
35	1	1	1	3	5	2	1	78	59	79

Table 3: RMSE of the NN model for the test set.

Sample No.		**4**	**7**	**16**	**21**	**26**	**30**	**32**	**RMSE**
Consumer Preferences	CU	63	52	62	41	58	68	61	
	AR	52	66	74	50	71	59	49	
	AT	54	61	72	58	68	65	51	
NN Predictions	CU	38.1	76.9	52.1	56.2	55.0	66.5	69.3	
	AR	50.6	68.5	65.4	67.1	65.6	59.4	49.2	0.0931
	AT	47.3	77.4	72.0	73.6	69.6	64.6	52.3	

Step 6: Obtain an overall preference value P_i for each design alternative C_i by (18).

Step 7: Rank 4,860 design alternatives by their P_i value to best match the desirable consumers' preferences. To illustrate, Table 4 shows the top 10 ranking design alternatives with ”extremely cute”, ”slightly artistic”, and ”moderately attractive”.

In addition, Table 5 shows their corresponding combinations of product form elements individually. The product designer can use a computer aided design (CAD) system to facilitate the product form design in the new characteristic toy development process. Table 6 shows the optimal combinations of form elements of the Top 1 and TOP 2 alternatives with ”extremely cute”, ”slightly artistic”, and ”moderately attractive”.

Table 6: The optimal combinations of form elements of the TOP 1 and TOP 2 alternatives.

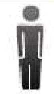
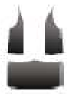
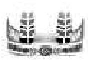
Form Element	TOP 1		TOP 2	
	Form Type	CAD	Form Type	CAD
Length ratio of head and body (X_1)	<1:2		<1:2	
Width ratio of head and body (X_2)	head>body		head>body	
Costume style (X_3)	robe		two-pieces	
Costume pattern (X_4)	simple		simple	
Headdress (X_5)	arc-shaped		feathered	
Appearance of facial features (X_6)	entire features		entire features	
Overall appearance (X_7)	cute style		cute style	

Table 4: The TOP 10 ranking design alternatives.

Ranking	No.	S_i^+	S_i^-	P_i
1	3643	0.2074	0.9427	0.8197
2	3454	0.2143	0.9566	0.8170
3	3631	0.2159	0.9453	0.8141
4	3265	0.2277	0.9649	0.8090
5	3442	0.2288	0.9513	0.8061
6	3274	0.2220	0.8999	0.8021
7	3262	0.2232	0.9032	0.8018
8	3619	0.2316	0.9367	0.8018
9	3634	0.2552	1.0044	0.7974
10	3451	0.2278	0.8923	0.7966

Table 5: The corresponding combinations of form elements of the TOP 10 alternatives.

Ranking	Form Elements						
	X_1	X_2	X_3	X_4	X_5	X_6	X_7
1	3	1	3	1	5	3	1
2	3	1	2	1	4	3	1
3	3	1	3	1	4	2	1
4	3	1	1	1	3	3	1
5	3	1	2	1	3	2	1
6	3	1	1	1	4	3	1
7	3	1	1	1	3	2	1
8	3	1	3	1	3	1	1
9	3	1	3	1	4	3	1
10	3	1	2	1	4	2	1

5 Conclusion

In this paper, we have demonstrated how a consumer-oriented approach can be applied to build an NN-based TOPSIS decision support model for helping product designers obtain the optimal alternatives (ideal solutions) that best meet consumers' preferences. With an experimental study on characteristic toys, we have shown how the characteristic toy design decision support model can support the product development process, in conjunction with a CAD system. Although characteristic toys are used as the experimental samples, the consumer-oriented approach presented can be applied to other consumer products with a wide variety of product form elements.

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References

[1] C. F. Chen, C. H. Yeh, and Y. C. Lin, Multiattribute decision support for eco-product form design. Proc. of the 22nd Chinese Control and Decision Conference (CCDC 2010), IEEE Computer Society, 4226-4231 (2010).

[2] C. F. Chen, C. H. Yeh, and Y. C. Lin, Consumer-oriented optimal eco-product form design. Proc. of 2010 International Symposium on Computer, Communication, Control and Automation (3CA 2010), IEEE Computer Society, 602-605 (2010).

[3] J. U. Kim, W. J. Kim, and S. C. Park, Consumer perceptions on web advertisements and motivation factors to purchase in the online shopping. Computers in Human Behavior, **26**, 1208-1222 (2010).

[4] H. H. Lai, Y. C. Lin, and C. H. Yeh, Form design of product image using grey relational analysis and neural network models. Computers and Operations Research, **32**, 2689-2711 (2005).

[5] H.-H. Lai, Y.-C. Lin, C.-H. Yeh, and C.-H. Wei, User oriented design for the optimal combination on product design. International Journal of Production Economics, **100**, 253-267 (2006).

[6] Y. C. Lin, H. H. Lai, and C. H. Yeh, Consumer-oriented product form design based on fuzzy logic: A case study of mobile phones. International Journal of Industrial Ergonomics, **37**, 531-543 (2007).

[7] Y. C. Lin, and C. C. Wei, An intelligent decision support model for product design. Smart Innovation, Systems and Technologies, Pro. of the 3rd International Conference on Intelligent Decision Technologies (IDT 2011), **10**, 833-842 (2011).

[8] M. Nagamachi, Kansei engineering: A new ergonomics consumer-oriented technology for product development. International Journal of Industrial Ergonomics, **15**, 3-10 (1995).

[9] M. Nagamachi, Kansei engineering as a powerful consumer-oriented technology for product development. Applied Ergonomics, **33**, 289-294 (2002).

[10] M. Negnevitsky, Artificial Intelligence. Addison-Wesley, New York, (2002).

[11] C. H. Yeh, H. Deng, and Y. H. Chang, Fuzzy multicriteria analysis for performance evaluation of bus companies. European Journal of Operational Research, **126**, 459-473 (2000).

[12] C. H. Yeh, and Y. H. Chang, Modeling subjective evaluation for fuzzy group multicriteria decision making. European Journal of Operational Research, **194**, 464-473 (2009).

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