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User-oriented design for the optimal combination on product design

Hsin-Hsi Lai[a], Yang-Cheng Lin[a,*], Chung-Hsing Yeh[b], Chien-Hung Wei[c]

[a]*Department of Industrial Design, National Cheng Kung University, Tainan 701, Taiwan*
[b]*School of Business Systems, Monash University, Clayton, Victoria 3800, Australia*
[c]*Department of Transportation and Communication Management Science, National Cheng Kung University, Tainan, 701 Taiwan*

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Abstract

This paper presents a new approach of user-oriented design for transforming users' perception into product elements design. An experimental study on mobile phones is conducted to examine how product form and product color affect product image individually and as a whole. The concept of Kansei Engineering is used to extract the experimental samples as a data base for Quantitative Theory Type I and neural networks (NNs). The result of numerical analysis suggests that mobile phone makers need to provide various product colors to attract users, in addition to product forms. This paper demonstrates the advantage of using NNs for determining the optimal combination of product form and product color, particularly if the product into design elements. Based on the analysis of NNs, we can use 72 representative product colors of each mobile phone to develop a product color data base consisting of 16777216 ($= 256 \times 256 \times 256$, True-Color model) colors with the associated product image. The design data base provides useful insights to save any amount of money and time for the new product development. The product designers can input a product image to work out an adequate color on a mobile phone. Furthermore, the design data base can be used, in conjunction with computer-aided design system or virtual reality technology, to build a 3D model for facilitating the design process of mobile phones. Although, the mobile phones are chosen as the object of the experimental study, this approach can be applied to other products with various design elements.

Keywords: User-oriented design; Product design; Perception; Kansei engineering; Neural networks

1. Introduction

The product image plays an important role in users' preference and choice of the product (Chuang et al., 2001). The concept of "user" can generally comprise two groups: the consumers and

*Corresponding author. Tel.: +886 6 2757575x54336 10; fax: +886 6 2746088.
E-mail address: lyc0914@cm1.hinet.net (Y.-C. Lin).

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the designers. However, the way that consumers look at product image is usually different from the way that designers look at product elements or characteristics (Hsu et al., 2000). Whether consumers choose a product depends largely on their perception of product image (Hsiao and Liu, 2002), while designers design a product by considering physical elements or characteristics of the product (Matsubara and Nagamachi, 1997). In addition, consumers' perception of product image is often a black box and cannot be precisely described (Chuang et al., 2001). To best meet consumers' need of a product from a design perspective, the physical elements of the product require being linked to consumers' perception of the product (Aitken et al., 2003). Consumer-oriented technologies (Fukushima and Kawata, 1995; Jindo et al., 1995; Karnes et al., 1995; Yun et al., 2003) have been developed to help designers design a desired product. In particular, Kansei Engineering (Nagamachi, 1989, 1995, 2002) has been developed as "translating technology of a consumer's feeling (Kansei in Japanese) and image of a product into design elements". It has been applied successfully in the product design field (Hsiao and Chen, 1997; Ishihara et al., 1995, 1997; Jindo and Hirasago, 1997; Kashiwagi et al., 1994; Tanoue et al., 1997; Yang et al., 1999; Youji and Tomio, 1995) to explore the relationship between the feeling (perception of product image) of the consumers and the design elements of the product (Perona and Saccani, 2004; Salvador and Forza, 2004).

Based on users' preference and perception, most product design studies on product image have focused on the relationship between product image and product form (Chuang and Ma, 2001; Hsiao and Liu, 2002; Hsu et al., 2000; Jindo et al., 1995). These studies develop a design support model or system (Kengpol, 2004; Lee et al., 2004) for product designers to find out the optimal design of product form. To allow designers to input an image word pair (e.g. for representing a design concept, such as the "simple" image product or the "modern" image product) to work out adequate components, some of these studies build a 3D model of product design using the computer-aided design (CAD) system (Hsiao and Chen, 1997; Jindo et al., 1995). In addition to product form, recent studies on product design have shown that the color element also has a great influence on users' perception of product image (Baxter, 1995; Fukushima and Kawata, 1995; Yun et al., 2003). To measure the influence of product color on users' perception, the concept of "color emotion" has been successfully used (Cheng, 2002; Nakamura et al., 1994; Xin and Cheng, 2000). As such, we need to consider both product form and product color, when dealing with the issue of users' perception of product image on product design (Baxter, 1995; Pawar and Driva, 1999; Tornberg et al., 2002).

In this study, we extend product image studies on product form to include product color. Hence, we focus on the relationship between product form and product color in terms of product image. Specifically, we will address the following research problems on the effect of form and color on product image. What kind of product form is suitable for a certain color? Are all product forms suitable for any color? Which has a greater influence on product image to the users? Does color affect product image and thus emotional feeling of the users? Is there an optimal combination of form and color for a given design concept of product image?

To illustrate how the relationship between product form and product color in terms of product image can be examined, we conduct an experimental study of mobile phones. The mobile phone is currently the most popular consumer product and exhibits wide variety in product form and color. In order to attract the users, particularly e-generations, the mobile phone industry has to provide variable styles of mobile phones, including outer shells with different colors.

Fig. 1 outlines our new approach using Kansei Engineering (Nagamachi, 1989, 1995, 2002) and numerical evaluation analysis, which will be presented in subsequent sections. The process of Kansei Engineering is used to extract experimental samples as numerical data sets required for analysis. We then use Quantitative Theory Type I (Nagamachi, 1989) to analyze the experimental data sets for answering the research questions, and measure the relative importance of product form

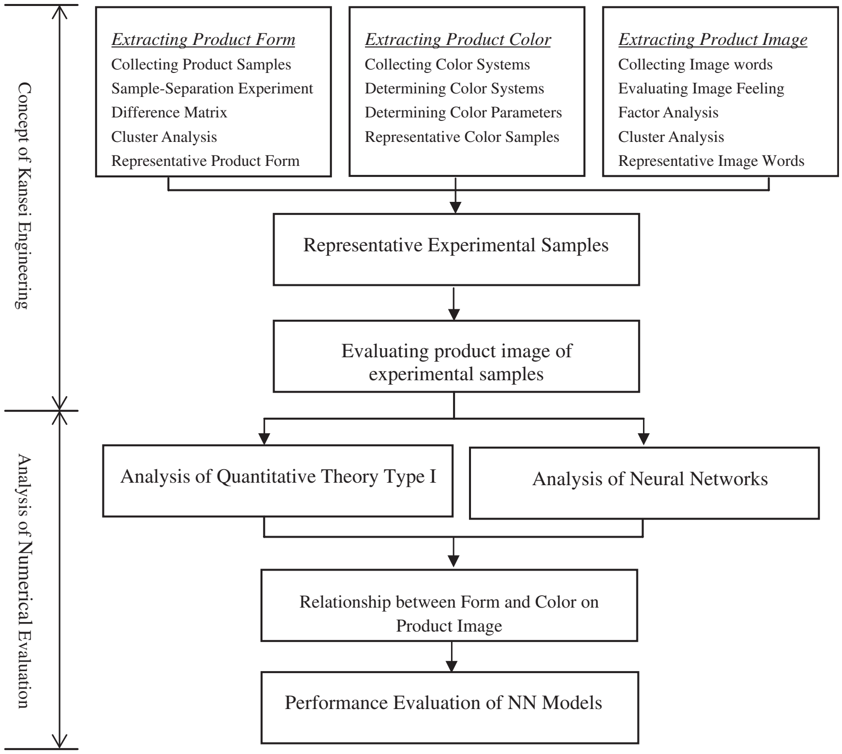

Fig. 1. The approach of this study.

and product color with respect to product image. To evaluate product image for any combination of product form and product color, we use neural networks (NNs) techniques (Golden, 1996) to formulate the process of user-oriented design of product image. NN models are developed to transform product form and product color into a set of product images perceived by users. Finally, we evaluate the performance of NN models in order to determine the best model that can be used to help product designers for matching a designated product image.

2. Kansei engineering for extracting experimental samples

The product image of users' perception is called "kansei" in Japanese. Kansei Engineering has been recently developed as a user-oriented technology for new product development (Nagamachi, 1995, 2002) and has been applied successfully in the product design field (Ishihara et al., 1997; Jindo and Hirasago, 1997; Kashiwagi et al., 1994; Matsubara and Nagamachi, 1997; Tanoue et al., 1997; Yang et al., 1999; Youji and Tomio, 1995). Kansei Engineering is a process of linking the users' feeling (Kansei) of a product, represented by image word pairs, to the product design elements, using a survey or an experiment (Nagamachi, 1995).

In this study, we use the concept of Kansei Engineering to extract the representative experimental samples, including product form samples, product color samples, and image word pairs of product image. We use product designers as subjects, because product designers are not only designing the products but also using the products. Product designers can clarify their needs or explain why they prefer particular product characteristics better than general users or consumers can. The subjects of the experiment consist of three groups of 15 product design experts each, assigned randomly. The first group has 8 males and 7 females for extracting the representative samples of mobile phones. The second group has 9 males and 6 females for evaluating the product image of the render experimental samples, as numerical data sets required for analysis. The third group has 7 males and 8 females for evaluating the performance of the NN models developed in this study.

2.1. Extracting product form samples

In order to facilitate the identification of representative samples of mobile phones in the market, we need to first classify mobile phones based on their similarity degree. This classification result can then be used to extract sample mobile phones for extracting product form samples and for subsequent models building and testing. This procedure involves the following nine steps:

Step 1: Select 30 mobile phones of various makers which entered the market during 1999–2001.

Step 2: Make 30 small paper cards according to the original size of each mobile phone.

Step 3: Separate 30 small paper cards into 7–12 groups by their similarity degree, based on the experimental result obtained from the 15 subjects of the first expert group using the Kawakida Jirou (KJ) method (Cross, 1994). The method was introduced by Kawakida Jirou in 1953 for classifying ideas, concepts, or objects into several groups. It has been successfully applied to a variety of classification problems.

Step 4: Build a similarity matrix from the separation result obtained at Step 3.

Step 5: Transform the similarity matrix into a dissimilarity matrix for the analysis at Step 6.

Step 6: Apply multiple dimension scaling (MDS) analysis (Hair et al., 1995) with the dissimilarity matrix data. To determine the most appropriate dimensionality for the data, we examine 5 different dimensional spaces (ranging from 2 to 6 dimensions), which are commonly used in empirical studies.

Step 7: Choose 5 dimensions as a result of the MDS analysis with Stress $= 0.097$ (smaller than 0.1) and RSQ $= 0.865$. In determining the dimensionality to use for a given set of data, a commonly used measure of fit in MDS is stress, which is the square root of a normalized residual sum of squares. A smaller stress value indicates a better fit. Another common measure of fit is the squared correlation (RSQ) value. The higher the RSQ value, the better the fit (Hair et al., 1995).

Step 8: Perform cluster analysis (Hair et al., 1995) with MDS, whose results are shown in Table 1. Sample numbers 7, 12, 14, and 23 are the cluster centers, as listed in the last two columns of Table 1.

Step 9: Use the 4 cluster centers of cluster analysis as the 4 representative mobile phone samples.

2.2. Extracting product color samples

The color system of Commission International de l'Eclairage (CIE) is chosen because its color space is more symmetrical than other color systems, such as Munsell color system and Ostwald color system (Danger, 1987; Wyszecki and Stiles, 1982). The color system of CIE comprises 3 attributes: Lightness (L^*), Chroma (C^*), and Hue (h°), respectively. With 3 attributes of color, 3 values of Lightness ($L^* = 30$, 50, and 70; $0 \leqslant L^* \leqslant 100$), 3 values of Chroma ($C^* = 20$, 40, and 60; $0 \leqslant C^* \leqslant 60$), and 8 values of Hue ($h^\circ = 0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ$, and 315°; $0^\circ \leqslant h^\circ \leqslant 360^\circ$) are selected to generate 72 ($= 3 \times 3 \times 8$) representative product color samples in this study. Fig. 2 shows these color samples.

In Fig. 2, the horizontal axis represents the "Red–Green" color, valued by parameter a^* ($-60 \leqslant a^* \leqslant 60$), and the vertical axis represents the "Yellow–Blue" color, valued by parameter b^* ($-60 \leqslant b^* \leqslant 60$). The degrees of Chroma (C^*) and Hue (h°) are determined by the values of a^* and b^*, as

$$C^* = \sqrt{a^{*2} + b^{*2}}, \tag{1}$$

$$h^0 = \tan^{-1} \frac{b^*}{a^*}. \tag{2}$$

Finally, each of the 4 representative mobile phones is rendered individually by 72 representative colors as experimental training samples, resulting in a total of 288 ($= 72 \times 4$) samples. In

Table 1
The results of MDS and cluster analysis

Sample	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Group no.	Distance
1	1.56	1.34	0.08	−0.94	−0.60	1	2.62
2	−0.89	1.20	−0.95	0.94	0.63	3	2.54
3	1.55	0.22	1.70	0.53	0.25	1	0.55
4	−1.23	0.77	−0.28	1.86	−0.37	3	2.45
5	−0.45	−1.83	−0.66	−0.53	−0.82	4	1.26
6	1.46	0.88	−1.02	−0.32	0.33	1	2.68
7	−0.26	−1.74	−0.31	0.43	−1.51	4	*0*
8	−0.14	−1.73	0.11	−0.74	0.87	2	1.81
9	1.25	−1.06	0.00	0.23	−1.26	4	1.72
10	−1.36	−0.95	0.04	−1.38	−0.01	2	2.56
11	−1.02	−0.90	−0.47	−0.83	0.73	2	1.47
12	−0.61	−0.83	−0.77	−0.04	1.87	2	*0*
13	−1.63	0.85	0.89	−1.00	−0.20	3	0.93
14	1.69	0.20	1.29	0.85	0.34	1	*0*
15	1.45	1.12	−1.00	−0.30	0.13	1	2.74
16	0.12	−0.02	1.53	2.15	−0.21	1	2.13
17	−1.94	1.04	0.72	−0.34	−0.36	3	0.19
18	0.46	−0.45	−1.07	0.81	1.78	2	1.45
19	0.01	−1.53	−1.38	0.10	−0.17	4	1.78
20	−0.57	−0.97	−1.50	0.96	−0.42	4	1.89
21	−0.94	1.55	−0.61	1.27	−0.07	3	2.31
22	0.95	−1.14	1.20	−0.23	1.16	1	2.05
23	−1.93	1.15	0.72	−0.23	−0.45	3	*0*
24	0.75	−1.25	1.89	0.46	0.29	1	1.87
25	1.38	−0.25	−0.41	0.03	−1.76	4	2.27
26	−1.89	0.65	0.33	−0.55	−0.07	3	0.80
27	1.86	1.14	0.03	−0.20	0.26	1	1.90
28	−1.69	1.09	0.08	−0.47	−0.06	3	0.83
29	1.19	1.51	−0.76	−0.65	−0.08	1	2.93
30	0.87	−0.05	0.56	−1.86	−0.22	1	2.98

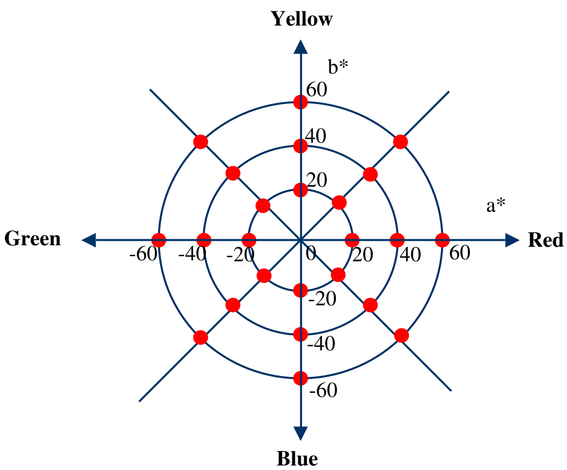

Fig. 2. Representative color samples with $L^* = 30$.

Table 2, Columns 1 and 7 list the numbers for these 72 color samples. Columns 2–5 and 8–12 list the corresponding attribute values of these color samples.

As an illustration, Fig. 3 shows 72 color samples of one representative mobile phone sample. The sample size of the color-rendered mobile phone is printed about $35\,\text{mm} \times 12\,\text{mm}$, and the view distance is about 300 mm, converted into a visual angle of about 2.5°.

2.3. Extracting image word pairs of product image

In Kansei Engineering, an image word pair represents a user's perception of a product (Nagamachi, 1995). In order to describe exactly

Table 2
The values of representative color samples

No.	L^*	a^*	b^*	C^*	h°	No.	L^*	a^*	b^*	C^*	h°
C01	30	60	0	60	0	C37	30	−60	0	60	180
C02	30	40	0	40	0	C38	30	−40	0	40	180
C03	30	20	0	20	0	C39	30	−20	0	20	180
C04	50	60	0	60	0	C40	50	−60	0	60	180
C05	50	40	0	40	0	C41	50	−40	0	40	180
C06	50	20	0	20	0	C42	50	−20	0	20	180
C07	70	60	0	60	0	C43	70	−60	0	60	180
C08	70	40	0	40	0	C44	70	−40	0	40	180
C09	70	20	0	20	0	C45	70	−20	0	20	180
C10	30	42	42	60	45	C46	30	−42	−42	60	225
C11	30	28	28	40	45	C47	30	−28	−28	40	225
C12	30	14	14	20	45	C48	30	−14	−14	20	225
C13	50	42	42	60	45	C49	50	−42	−42	60	225
C14	50	28	28	40	45	C50	50	−28	−28	40	225
C15	50	14	14	20	45	C51	50	−14	−14	20	225
C16	70	42	42	60	45	C52	70	−42	−42	60	225
C17	70	28	28	40	45	C53	70	−28	−28	40	225
C18	70	10	14	20	45	C54	70	−14	−14	20	225
C19	30	0	60	60	90	C55	30	0	−60	60	270
C20	30	0	40	40	90	C56	30	0	−40	40	270
C21	30	0	20	20	90	C57	30	0	−20	20	270
C22	50	0	60	60	90	C58	50	0	−60	60	270
C23	50	0	40	40	90	C59	50	0	−40	40	270
C24	50	0	20	20	90	C60	50	0	−20	20	270
C25	70	0	60	60	90	C61	70	0	−60	60	270
C26	70	0	40	40	90	C62	70	0	−40	40	270
C27	70	0	20	20	90	C63	70	0	−20	20	270
C28	30	−42	42	60	135	C64	30	42	−42	60	315
C29	30	−28	28	40	135	C65	30	28	−28	40	315
C30	30	−14	14	20	135	C66	30	14	−14	20	315
C31	50	−42	42	60	135	C67	50	42	−42	60	315
C32	50	−28	28	40	135	C68	50	28	−28	40	315
C33	50	−14	14	20	135	C69	50	14	−14	20	315
C34	70	−42	42	60	135	C70	70	42	−42	60	315
C35	70	−28	28	40	135	C71	70	28	−28	40	315
C36	70	−14	14	20	135	C72	70	14	−14	20	315

users' perception of mobile phones, we need to collect a large set of image word pairs with respect to product image. The procedure of extracting image word pairs includes the following four steps:

Step 1: Collect a large set of image word pairs from magazines and product catalogs. In this study, we collected more than 100 image word pairs.

Step 2: Evaluate collected image word pairs using the semantic difference (SD) method (Osgood and Suci, 1957).

Step 3: Apply factor analysis (Hair et al., 1995) and cluster analysis to the result of SD obtained at Step 2.

Step 4: Determine 3 representative image word pairs of product image, including Simple–Complex (S–C), Handsome–Rustic (H–R), and Leisure–Formal (L–F), based on the analyses performed at Step 3 (Guan and Lin, 2001).

The above results have been reported in our prior studies (Guan and Lin, 2001; Lin et al., 2001).

Fig. 3. The color-rendered samples of one representative mobile phone.

2.4. Evaluating product image of experimental samples

To evaluate 288 ($=72\times4$) rendered mobile phone samples by 3 representative product images, there are 864 ($=288\times3$) product image evaluations to separate into 12 sections ($12\times72=864$). Each subject evaluates one section (with 72 rendered mobile phone samples), takes a short break, then evaluates another section, takes a short break, and so on, until all 12 sections are completed. The 15 subjects of the second expert group are involved in the experimental evaluation of Kansei Engineering (Nagamachi, 1995). In Kansei Engineering, surveys or experiments are conducted to grasp the users' perception (psychological feeling and image) about a new product. To describe a specific image of mobile phones in terms of users' ergonomic and psychological estimation, a pair of image words is often used. Based on our prior study (Guan and Lin, 2001; Lin et al., 2001), we use 3 representative image word pairs for describing product images of mobile phones, which are Simple–Complex (S–C), Handsome–Rustic (H–R), and Leisure–Formal (L–F). To obtain the evaluation values for the 3 product images, a 7-point scale (1–7) of the semantic difference (SD) method (Osgood and Suci, 1957) is used. For example, the 15 subjects are asked to assess product image (look) of mobile phones on a simplicity–complexity scale of 1–7, where 1 is most simple and 7 is most complex.

The evaluation results of the 864 representative experimental samples by the 15 subjects provide a numerical data source for applying Quantitative Theory Type I (Nagamachi, 1989) and NNs (Golden, 1996) techniques to answer the research questions identified in this study. To help how these questions are dealt with, these techniques are described in the following section.

3. Quantitative Theory Type I for measuring relative importance of product image

We use Quantitative Theory Type I analysis to examine the degree of relative importance of product form and product color, including 4 product elements (form and 3 color attributes), on product image. Quantitative Theory Type I (Nagamachi, 1989) is a technique of multiple regression analysis for deducing a quantitative variable (a dependent variable) from some qualitative variables (independent variables). In this study, 4 independent variables (X_1, X_2, X_3, and X_4) are used to represent one form (phone style) and 3 color attributes (Lightness, Chroma, and Hue). And, 3 dependent variables (Y_1, Y_2, and Y_3) are used as the average of product image evaluations on the 3 image word pairs, respectively. The result of Quantitative Theory Type I analysis is given in Table 3.

In Table 3, the correlation coefficients indicate the relationship between 4 variables of products (X_1, X_2, X_3, and X_4) and each product image (Y_1, Y_2, or Y_3). For example, the highest variable of the partial correlation coefficient in the "S–C" image is the "lightness" variable ($X_2 = 0.866$), meaning that "lightness" primarily affects the "S–C" image of the product. In addition, Table 3 shows that "lightness" also affects the "L–F" image, but the "Hue" variable mainly influences the "H–R" image. The "Chroma" variable is the least-significant one on the 3 image word pairs among Lightness, Chroma and Hue. In the last two rows of Table 3, R means the correlation between the observed and predicted values of the dependent variable, and R^2 is the square of this correlation. R^2 ranges from 0 to 1. If there is no linear relation between the dependent variable (Y_1, Y_2, or Y_3) and independent variables (X_1, X_2, X_3, and X_4), R^2 is 0 or very small. Otherwise, if all the values fall on the regression line, R^2 is 1. In addition, R^2 is also called the coefficient of determination (Hair et al., 1995).

The category grades shown in Table 3 indicate the preference degree of the user perception on the each category of independent variables. If the grade is negative, the user perception leans towards the left image. On the contrary, the positive grade indicates that the user perception favors the right image. For example, the category grades of 3 selected values of lightness in the "S–C" image are 0.696, −0.047, and −0.648, respectively. The result shows that the user perception prefers the "complex" image when $L^* = 30$,

Table 3
The results of Quantitative Theory Type I

Element	No./value	Simple–Complex (Y_1)		Handsome–Rustic (Y_2)		Leisure–Formal (Y_3)	
		Category grade	Partial c. c.	Category grade	Partial c. c.	Category grade	Partial c. c.
Form	7	−0.129	*0.292*	0.134	*0.261*	0.007	*0.126*
(X_1)	12	−0.056		0.072		0.018	
	14	0.080		0.011		0.066	
	23	0.106		−0.217		−0.091	
Lightness	30	0.696	*0.866*	0.551	*0.669*	0.859	*0.846*
(X_2)	50	−0.047		−0.021		0.021	
	70	−0.648		−0.530		−0.880	
Chroma	60	−0.101	*0.300*	−0.154	*0.342*	−0.200	
(X_3)	40	−0.034		−0.096		−0.070	
	20	0.136		0.250		−0.270	
Hue	0	−0.077	*0.674*	−0.317	*0.740*	−0.285	*0.552*
(X_4)	45	0.117		−0.057		0.201	
	90	0.569		1.165		0.652	
	135	0.180		0.146		0.044	
	180	−0.070		0.195		0.048	
	225	−0.448		−0.752		−0.220	
	270	−0.295		−0.486		−0.264	
	315	0.025		0.105		−0.176	
Constant		3.948		3.895		3.542	
		$R = 0.895$		$R = 0.831$		$R = 0.872$	
		$R^2 = 0.801$		$R^2 = 0.691$		$R^2 = 0.761$	

and favors the "simple" image when $L^* = 50$ or 70. That is, the darker the product color, the more complex the perceived product image.

The partial correlation coefficients of form (X_1) on the 3 image word pairs (0.292, 0.261 and 0.126, respectively) are the lowest among the 4 product variables. Table 3 shows the color variable is more important than the form variable on product image. As a result of Quantitative Theory Type I analysis, the 3 models given below indicate the relationship between product form and product color on a set of product image for the 3 image word pairs, respectively.

$$Y_1(\mathrm{S}-\mathrm{C}) = 0.292X_1 + 0.866X_2 + 0.300X_3 + 0.674X_4 + 3.948, \quad (3)$$

$$Y_2(\mathrm{H}-\mathrm{R}) = 0.261X_1 + 0.669X_2 + 0.342X_3 + 0.740X_4 + 3.895, \quad (4)$$

$$Y_3(\mathrm{L}-\mathrm{F}) = 0.126X_1 + 0.846X_2 + 0.405X_3 + 0.552X_4 + 3.542. \quad (5)$$

We can use these 3 models to input the values of 4 product variables, and then output the prediction value of product image. These models can help the product designers understand users' perception of form and color for the corresponding product image. These models can also be used to examine the effect of the corresponding product image for a given combination of form and color. Table 4 shows the design support information for product designers to find out the optimal combination of form and color in terms of a given product image.

Table 4
Optimal combinations of product form and product color

	Simple	Complex	Handsome	Rustic	Leisure	Formal
Form	7	23	23	7	23	14
Lightness	70	30	70	30	70	30
Chroma	60	20	60	20	60	20
Hue	225	90	225	90	0	90

4. NNs for evaluating the optimal combination of product image

NNs techniques are non-linear models and are widely used to examine the complex relationship between input variables and output variables (Golden, 1996). Based on the notion that the process of product design or the perception of the users is a "black box" or involves "uncertain information," we use NNs to evaluate product image for any combination of product form and product color. Due to their effective learning ability, NNs have been applied successfully in a wide range of fields, using various learning algorithms (Cavalieri et al., 2004; Eberts and Habibi, 1995; Hsu et al., 1999; Jin et al., 1996; Schikora and Godfrey, 2003; Wei, 2001). In this study, we use the multilayered feedforward NNs trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm (Golden, 1996). A multilayer network normally composes of many neurons in several layers. There are usually one input layer and one output layer, and typically one hidden layer between them (Negnevitsky, 2002), as shown in Fig. 4.

There are two modes of operation for the backpropagation NN model—the training process and the test process (Negnevitsky, 2002). During the training process, NNs take the training samples and then check the training process repeatedly. The test process is the prediction by evaluating the possible result of another sample set, based on the training result. In order to examine whether the NN model is an effective technique for determining the optimal combination on product design for matching a desirable product image, we develop

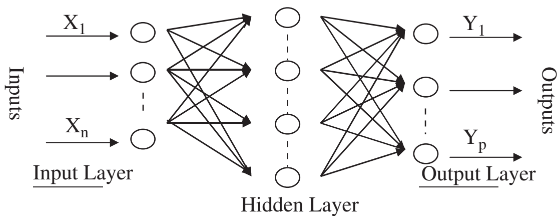

Fig. 4. The structure of NNs.

two NN models for the training process, called mixed-NN model and single-NN model, respectively, in our experimental study.

4.1. The mixed-NN model

The 4 product forms (phone style, the 4 representative mobile phone samples) and 3 color attributes (L^*, C^*, and $h°$), as those used in the Quantitative Theory Type I analysis, are the 7 input neurons of the mixed-NN model. The average values of 3 image word pairs are used as the 3 output neurons. The number of neurons of the hidden layer used in both the mixed-NN and single-NN models is determined by (the numbers of input neurons + the numbers of output neurons)/2, which is the most widely used rule (Golden, 1996). The learning rule used is Delta-Rule and the transfer function is Sigmoid (Golden, 1996). Table 5 lists the neurons of the two NN models, including the input layer, hidden layer, and output layer.

Totally 288 experimental samples were used as the training samples. Each model trained 1000 epochs at each run. In this study, when the cumulative training epochs were over 5000, the root of mean square (RMS) errors was convergent, and the training process was thus completed. The third row of Table 6 shows the training epochs of each model run and their corresponding RMS errors.

4.2. The single-NN model

The single-NN model is used for training the 4 representative mobile phones individually with 72 experimental samples, thus having a total of 4 training processes. The input variables are the 3 color attributes (L^*, C^*, and $h°$). The 3 output neurons used are the same as the mixed-NN model. There is one hidden layer with 3 neurons.

In this study, when the RMS errors are smaller than 0.05, the training process is completed. In order to avoid local optimum, the training process is continued until the RMS errors are also smaller than the smallest value previously obtained. The last four rows of Table 6 give the training epochs and their corresponding RMS errors. As shown in Table 6, the lowest RMS errors of the single-NN model (0.0335, 0.0329, 0.0263 and 0.0182, respectively) are all smaller than the mixed-NN model (0.0851). The result indicates that 4 single-NN models have the highest training consistency on the given product image. The result suggests that the 4 single-NN models are the better models for transforming users' perception into product design in this study. To examine the performance of two types of NN models, we perform the test on all the models in the following section.

Table 5
The neurons of the two NN models

The mixed-NN model	Input layer: 7 neurons, including 4 mobile phone forms and 3 color attributes Hidden layer: 5 neurons, $(7+3)/2=5$ Output layer: 3 neurons, including 3 image word pairs
The single-NN model	Input layer: 3 neurons, including 3 color attributes Hidden layer: 3 neurons, $(3+3)/2=3$ Output layer: 3 neurons, including 3 image word pairs

5. Performance evaluation of the mixed-NN and single-NN models

In order to examine if the two NN models can be applied to new samples, 12 samples of new colors of mobile phones are created as the test samples. The values of new color samples are given in Table 7. In the test process, the 15 subjects of the third expert group are involved using a 7-point scale (1–7) of SD method (Osgood and Suci, 1957). Each subject evaluates 12 rendered mobile phone samples by 3 representative image word pairs, totally 36 ($=12\times3$) product image evaluations. Table 8 shows the prediction results of the two NN models and evaluation results of the subjects' perception. We use a t-test to examine if the NN models' prediction results are different from the subjects' evaluation results, which are averaged as standard values. If the P-value of t-test is greater than 0.05, there is no significant statistical

Table 6
The RMS errors of the two NN models

Model		Training epochs				
		1000	2000	3000	4000	5000
Mixed-NN model		0.1004	0.0876	0.0868	0.0860	*0.0851*
Single-NN model	-Phone 7	0.1398	0.0939	0.0486	0.0673	*0.0335*
	-Phone 12	0.1336	0.0502	0.0421	*0.0329*	
	-Phone 14	0.1440	0.0346	0.0450	0.0551	*0.0263*
	-Phone 23	0.0280	0.0446	0.0352	*0.0182*	

Table 7
The values of 12 new color samples

No.	L^*	a^*	b^*	C^*	h°	No.	L^*	a^*	b^*	C^*	h°
N01	20	17	10	20	30	N07	20	−17	−10	20	210
N02	40	34	20	40	30	N08	40	−34	−20	40	210
N03	60	51	30	60	30	N09	60	−51	−30	60	210
N04	20	−10	17	20	120	N10	20	10	−17	20	300
N05	40	−20	34	40	120	N11	40	20	−34	40	300
N06	60	−30	51	60	120	N12	60	30	−51	60	300

difference between the models' prediction and the subjects' perception.

Table 8 shows that the single-NN model (total consistency = 72.22% ($\frac{26}{36}$), as 26 P-values are more than 0.05 with 12 samples by 3 image word pairs) has a higher consistency than the mixed-NN model (total consistency = 63.89% ($\frac{23}{36}$). The total consistency means the correlation between the models' prediction and the subjects' perception. The total consistency ranges from 0% to 100%. If there is higher consistency between the models' prediction and the subjects' perception, the total consistency is close to 100% (the highest prediction rate). This result is in accord with the result of the RMS errors of the single-NN model in Table 6, both being smaller than the mixed-NN model. The result suggests that the single-NN model is a better model for transforming users' perception into product elements design in this study.

In terms of image word pairs, the two NN models have the highest predictive consistency on the "Simple–Complex" image, with both models' total consistency being 91.67% ($\frac{11}{12}$), due to 11 P-values being more than 0.05 with 12 test samples. However, both are inconsistent on the "Leisure–Formal" image, with both models' consistency being 50.00% ($\frac{6}{12}$). This result was confirmed by another thorough investigation of a group of expert subjects. Half of the subjects regarded the pure color samples (the value of C attribute = 60) as having the "Leisure" image, while the other half of the subjects felt that these samples had the "Formal" image.

The results obtained from the back-propagation NN models can be used to help product designers to work out the optimal combination of product form and product color for a particular design concept represented by a product image word pair such as Simple–Complex. The product designer can focus on the determination of a desirable product image, and the NN models can help determine what combination of form and color can best match the desired product image. A product color data base based on product orm design consisting of 16 777 216 ($=256\times256\times256$, True-Color model) colors with the associated product image can be built using NN models. The designers can input a product image to work out adequate color on a mobile phone. To illustrate, Fig. 5 shows the optimal combinations

Table 8
The results of NN prediction and *T*-testing

New color samples	N01	N02	N03	N04	N05	N06	N07	N08	N09	N10	N11	N12
A single-NN mode1												
S–C prediction	4.52	4.30	3.24	4.68	4.22	3.87	5.10	4.71	3.41	5.27	4.65	3.69
T-value	−0.76	−2.72	−0.13	1.53	0.86	−1.45	−0.68	−2.10	0.29	−0.49	−0.23	1.08
P-value	0.46	*0.02*	0.89	0.15	0.41	0.17	0.51	0.05	0.77	0.63	0.82	0.30
	Average prediction rate: 91.67% ($\frac{11}{12}$)											
H–R prediction	4.71	4.49	3.53	4.75	4.35	4.04	4.67	4.44	3.39	5.00	4.33	3.27
T-value	−1.28	0.85	1.73	−3.06	−4.05	−1.40	1.63	0.01	−1.85	1.45	−5.61	−0.59
P-value	0.22	0.41	0.10	*0.01*	*0.00*	−0.60	0.64	1.00	−0.79	0.17	*0.00*	0.56
	Average prediction rate: 75.00% ($\frac{9}{12}$)											
L–F prediction	4.48	4.15	2.94	4.56	3.94	3.52	4.90	4.40	2.88	5.16	4.27	2.86
T-value	−0.40	−2.78	−5.26	−0.27	−1.17	−4.47	0.49	−3.55	−3.49	−1.61	−4.13	−0.72
P-value	0.69	*0.01*	*0.00*	0.79	0.26	*0.00*	0.63	*0.00*	*0.00*	0.13	*0.00*	0.48
	Average prediction rate: 50.00% ($\frac{6}{12}$)											
	Total prediction rate: 72.22% ($\frac{26}{36}$)											
A mixed-NN model												
S–C prediction	4.71	4.24	3.25	4.77	4.40	3.82	5.03	4.67	3.45	4.98	4.58	3.59
T-value	−1.21	−2.56	−0.17	1.25	0.30	−1.22	−0.46	−1.96	0.14	0.48	−0.05	1.35
P-value	0.25	*0.02*	0.87	0.23	0.77	0.24	0.65	0.07	0.89	0.64	0.96	0.20
	Average prediction rate: 91.67% ($\frac{11}{12}$)											
H–R prediction	4.49	4.49	3.36	4.52	4.33	4.17	4.71	4.54	3.14	4.52	4.14	3.41
T-value	−0.80	0.82	2.20	−2.47	−3.99	−1.71	1.52	−0.25	2.77	2.88	−4.95	0.28
P-value	0.43	0.42	*0.04*	*0.03*	*0.00*	0.11	0.15	0.80	*0.01*	*0.01*	*0.00*	0.78
	Average prediction rate: 50.00% (($\frac{6}{12}$)											
L–F prediction	4.60	4.24	2.77	4.66	4.13	3.58	4.90	4.50	2.80	4.80	4.15	3.03
T-value	−0.68	−3.06	−4.20	−0.51	−1.67	−4.70	0.51	−3.87	−3.24	−0.80	−4.50	−1.25
P-value	0.51	*0.01*	*0.00*	0.62	0.12	*0.00*	0.62	*0.00*	*0.01*	0.44	*0.00*	0.23
	Average prediction rate: 50.00% ($\frac{6}{12}$)											
	Total prediction rate: 63.89% ($\frac{23}{36}$)											
Subjects' perception												
S–C questionary	4.19	3.38	3.19	5.13	4.50	3.50	4.88	4.06	3.50	5.13	4.56	4.13
Standard deviation	1.72	1.36	1.47	1.15	1.32	1.03	1.31	1.24	1.26	1.20	1.55	1.59
H–R questionary	4.13	4.75	4.19	3.56	3.38	3.44	5.31	4.44	4.31	5.50	2.75	3.50
Standard deviation	1.82	1.24	1.52	1.55	0.96	1.71	1.58	1.59	1.70	1.37	1.13	1.32
L–F questionary	4.31	3.25	2.13	4.44	3.50	2.31	5.06	3.25	1.88	4.44	2.69	2.63
Standard deviation	1.66	1.29	0.62	1.75	1.51	1.08	1.29	1.29	1.15	1.79	1.54	1.31

of product form and product color for a set of product images represented by the S–C, H–R, and L–F values of 2, which is the closest among all combinations. Furthermore, the design-supporting results in this study can be used, in conjunction with computer-aided design (CAD) system or the virtual reality (VR) technology if needed, to build a 3D model for facilitating the design process of mobile phones.

6. Conclusion

In this paper, we have presented a new approach for transforming users' perception into product elements design, with an experimental study of mobile phones. We have used the concept of Kansei Engineering to extract the representative experimental samples of mobile phones. We have conducted Quantitative Theory Type I analysis to

Fig. 5. The optimal combinations of product form and product color.

examine how product form and product color may affect product image of mobile phones. The result of the analysis shows that product color is more influential than product form on product image of mobile phones. This result seems to suggest that mobile phone makers need to provide users with various product colors, in addition to product forms. Based on Quantitative Theory Type I analysis, the result also indicates that all product forms are not suitable for any color. Users prefer a certain color with respect to a desirable image, if the product form is already decided by themselves. The 3 models developed for the "Simple–Complex", "Handsome–Rustic", and "Leisure–Formal" images can be used to predict the value of product image for a given set of form and 3 attributes of color. These models can help the product designers better understand users' perception of product form and product color.

We have developed two NN models to suggest the optimal combination of product form and product color on product design for a given design concept represented by a product image word pair. The verification of both NN models shows that the single-NN model has a higher consistency than the mixed-NN model. Both NN models have the highest predictive consistency on the "Simple–-Complex" image, as compared to the "Handsome–Rustic" and "Leisure–Formal" images.

The results of this study provide useful insights in designing form and color of a product for enhancing the image of the product. These design-supporting results would help product designers work out the optimal combination of product form and product color on product image. Although, mobile phones are chosen as an illustration of the approach, the approach can be applied to other products with various design elements.

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