A Study of the Illustrative Style Effect of Icon Design – Using the Digital Camera Icon as an Example

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Three main questions are addressed in this study: (a) how do different icon design conditions (illustrative styles and design elements) and colours affect consumers' Kansei? (b) how do different design conditions and colours match with the icon image? and (c) what kind of design conditions and colours would generate positive influences on the icon image? To address these questions, the design conditions of icons as visual illustrative styles were defined, including "shadow style", "perspective style", "emboss style" *and* "frame style". *Three design elements were also arranged for each illustrative style, and a series of new icon samples were generated through Orthogonal Design. In addition, the new icon samples were assorted with the following colours,* Red, Orange, Yellow, Yellow-Green, Green, Cyan, Blue, Purple, *and were re-designed into on-line questionnaires. Subjects were asked to complete an icon image evaluation. Finally, the evaluation results were analyzed using Conjoint analysis and Neural networks. The RMSs of all the NN-based models and CA models are very small and the predicting performance of NN-based models and CA models are equally good.*

Keywords: Icon design, illustrative styles, design elements, Kansei Engineering, Neural networks, Conjoint analysis

1. INTRODUCTION

In keeping with the trend toward digitalized interface in consumer products, the use of icons has become a design strategy that can increase users' interest, help them to learn and stimulate their motivation to learn. As icon design is well diversified, the illustrative styles applied to screen design that are intended to maximize affective response from users has become a critical issue in screen design. For example, digital products can show many types of icons no matter whether two-dimensional, three-dimensional, virtual, audio or video, or dynamic on the display and these styles not only facilitate icon usage but also strengthen their functions. Therefore, screen design has become an important aspect of the design field recently. Furthermore, people make strong and broad demands on the various kinds of icons.

In terms of icon design or interface design, "user-centred design" is the current design trend. It is more important for designers to create or redesign new products according to perceptual demand by developing and applying new techniques. Recently, studies of *Kansei Engineering* have been promising, focusing on the interactions among people from the point of view of engineering. They attempt to translate consumers' feelings regarding products or other stimuli into concrete design

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elements. Furthermore, Kansei engineering research can help designers really understand users' needs and preferences. However, comprehensive graphic design of a product's display would evoke consumers' purchasing desire, attract learners' attention, and increase their interest (Levin *et al*, 1987). Therefore, when it comes to designing displays, we should focus on both the factors that influence consumers' feelings and the interactions between users and systems, such as overall appearance, colour allocation, size of characters, icon shapes, and dynamic or static icons.

Kansei engineering is a technique that not only transforms consumers' needs and feelings into product design elements, but also formulates the images of particular products in customers' minds (Nagamachi, 1995). It is also a method of transforming or relating consumers' feelings regarding products into design elements. In other words, Kansei engineering explores the corresponding layers between human beings' psychological and physiological feelings, and design elements. In practical terms, Kansei engineering has been broadly used by several businesses in Japan and all over the world for designing car seats (Nakada, 1997), office seats (Jindo *et al*, 1995), car decoration (Jindo and Hirasago, 1997), allocation of upholstery (Tanoue *et al*, 1997), and colours of product exteriority (Fukushima *et al*, 1995). However, most researchers in icon design still devote their efforts to icon recognition (Baber and Wankling, 1992). They emphasize how to apply related psychological theories to icon design based on recognition psychology. Basically, icons should be designed in accordance with the following principles, *visibility*, *legibility*, *readability*, *intention and simplicity* to meet the needs of *visual recognition*, *attention*, *shape-discrimination*, *and memory*. By means of texts, icons and text-icons on displays, we can evaluate the accuracy rate and task time of users' icon recognition. In this way, we can explore how users interact with various icon designs on the screen (Jindo and Hirasago, 1997).

In the overall design of the screen, the icon is the communication and learning tool that people rely on. The functions of icon communication include the design of the icon itself and its presentation. As a result, designers must pay more attention to the communicative function of icons (Saunders, 1994). Moreover, the processes by which users operate the display icons and how they learn from them play an important role. Consequently, it is another critical issue to understand the relationship between the user's interactions and the representation of icons (Chanlin, 1997). Rieber (1995) demonstrated that from the point of view of design, if icons that were well-designed visually failed to generate effective communication, they wouldn't direct users to notice important information no matter how visually creative they were. Furthermore, improper visual design could impose a greater mental burden on users or interrupt their concentration.

Regarding the conditions of icon design and the effects which icons have on users, studies concerned with how visual elements affect user's Kansei are rare. This shows that there is a huge potential for exploration or future application of the relevant topics of digitalized display design allocation and icon design, under the scope of Kansei engineering.

In this study, icon designs in digital cameras are used as an example of the exploration of the above-mentioned issues due to the following three reasons: (a) As for icon design, the icon itself embeds communicative, cognitive, and introductory functions. Besides, it provides conceptual expressions of mental models as well as assistance to memory. When an icon is put on the display, it also quickly attracts users' attention, becomes the focus of their attention, and directly influences their feelings. (b) Of the same type of shapes of icons, the change of different icon design conditions often affects user's perceptions towards icons. For instance, the icons in a series of versions of Internet Explorer, which uses shadow and emboss effects, and the "table icons" in Windows of PC and in the OS for Mac, which was modified by perspective and shadow effects, apply different design elements to satisfy users' feelings by transfiguring the icons on displays. (c) Users' impressions of an icon can be generally covered by positive and negative affect. Further, the motivation of designers is to maximize users' positive affect. As a result, we measured users' positive affect and discussed their "*Kansei*" in this study.

The purposes of this study are as follows:

1. Answer the question, how do different design conditions (illustrative styles and design elements) and colours of icon influence users' perceptions of icon design?
2. By applying conjoint analysis and neural networks, find out which kinds of design items and categories affecting the icon image are most significant.
3. Determine what kind of analytical skills would help designers to form the best portfolio of icon designs.

2. LITERATURE REVIEW

Literature referred to in this study includes Kansei engineering, icons, related investigative methods and analysis technology. A review of references according to different subjects appears below.

2.1. Kansei Engineering

Promoters of Kansei engineering usually rely on the Japanese scholar Mitsuo Nagamachi, but the actual person that invented the term Kansei engineering was the president of Japan's Mazda motor corporation, Kenichi Yamamoto. He gave a speech saying that the automobile must make some contribution to culture at the world automotive technology meeting in 1986, and used the tactics of Kansei engineering to design the feel of seat and automobile interior decoration, which satisfied passengers' needs and kansei requests. In addition, Mitsuo Nagamachi set up an "Emotion Technology Department" and carried on relevant research in the 1970s, but the word "emotion" could not elicit a sympathetic response. In the end, emotion engineering was renamed Kansei engineering in 1988, and the research results over the past seventeen years were published at the meeting of the tenth international human engineering conference, and the term caught the attention of many countries around the world (Miyazaki *et al*, 1993).

Therefore, Kansei engineering can be defined as:"a kind of technology to quantify people's perception of things (products), and to explore which design elements can relatively satisfy people's Kansei." The 'Kansei' of Kansei engineering can be described as the feeling or image which people have of the product and their expectations of the thing that they experience. Kansei engineering has already been extensively applied by business circles in Japan, including the design of the automobile exterior "look"(Yamamoto *et al*, 1986), and related design questions. In this research project, we conducted an experimental study using the concept of Kansei engineering to investigate the relationship between an image word pair and a design element of icon design. The subjects of the experiment consisted of three groups of icon design experts. The first group included eight males and seven females for extracting representative samples of icons.

2.2. Icon

The icon is a non-legible association of visual factors, used to express a certain view. The icon can further the cognitive disparity of the information transmission. The icon designer encodes the materials which they want to express to transform into the icon and transmit out via the media. Then the course of decoding of receiving and the message is finished by the user. The encoding process is icon design, and the course of decoding is understanding the icon.

The icon usually takes on a dominant role during the process of operating and studying the interface between the user and icons. It is also very important to understand how users interact with icons and to consider how icons appear (ChanLin, 1997). Furthermore, it may impose a burden on the user's memory or distract them, because of improper visual design. So, offering appropriate and good application mechanism in the design of the icon and making users understand the function meaning represented by the icon, could result in good information transmission and attain the man-machine interdynamic purpose.

A symbol (icon) performs an important assisting role in visual communication. It includes concrete symbols, abstract symbols, and two kinds of mixing types. The characteristics are: (1) numerical use on a Human-Computer-Interface button and guided mark, and is an indispensable key element for transmission, (2) surmount any deficiency by communicating with characters (words), it could effectively complete transmission, (3) to be an auxiliary operation explanation, and improve the recognizability of the button.

Riding and Ashmore (1980) claim that the cognitive style of Verbal-Imagery is related to the mode of information expression. They found that cognitive style influenced the course of information processing and individual preference in expression. So people could be arranged into two groups: verbal type people are used to consider anything they read, see, and hear in words; imagery type people would spontaneously feel the intelligence icon at the same time as they read, saw, or heard something. The difference between verbal types and imagery types are their preference for receiving information in either characters or icons. Therefore, it is necessary to consider these different points when we want to convey information.

2.3 Conjoint Analysis

Conjoint analysis refers to a number of different approaches, all of which use peoples' statements of how they would respond to different hypothetical situations. The term "conjoint analysis" means the breaking down of individual evaluations, within a designed set of multi-attribute alternatives, into separate components of utility (Reutterer and Kotzab, 2000). In conjoint analysis, the analyst specifies the levels for each attribute and then asks the respondent only for their overall preference. In this way, conjoint analysis is able to divide the preferences to determine the value of each attribute (Green and Krieger, 1996).

The word "conjoint" is used because the relative values of attributes considered jointly can be determined even though they might not be measurable if taken one at a time (Churchill, 1991). In conjoint analysis, the characteristics (key dimensions) of a product are described in terms of attributes. Variations within an attribute are described as levels and attribute levels represent the values of the independent variables (Reddy *et al*, 1995).

For each level of attributes, a part-worth value is computed. Large part-worth values are assigned to the most preferred levels, and small part-worth values are assigned to the least preferred levels. The attributes with the largest part-worth range are considered the most important in predicting preference. For subsequent analysis, the part-worth estimates can serve as a basis for predicting the choice probabilities of various combinations of attribute levels. Figure 1 provides a brief outline of the steps involved in a conjoint study.

In contrast to other multi-attribute models frequently employed in the measurement of product images, conjoint analysis represents a de-compositional technique for deriving part-worth estimates associated with selected aspects or attributes of a choice alternative on the basis of the overall preference statements of a group of respondents

In conjoint analysis, *factorial design* means that all of the portfolio of attributes and levels can be regarded as samples (stimulus) evaluated by subjects if the quantity of attributes and levels is not too

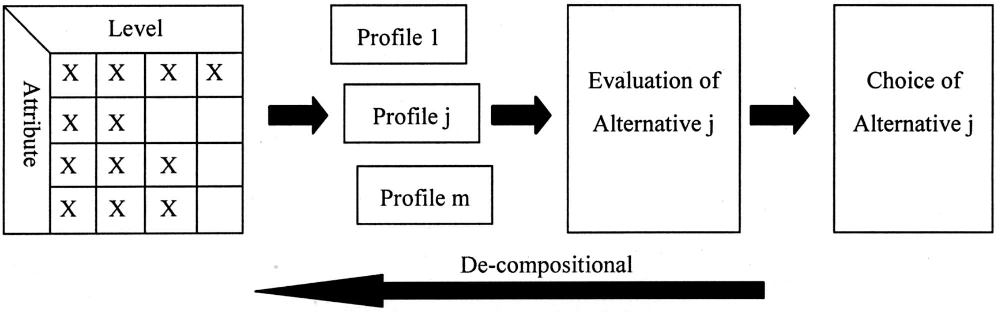

Figure 1: Conceptual framework of conjoint-analysis (Reddy *et al*, 1995)

large when analysts created them. However, on the other hand, factorial design could cause subjects to fail in evaluation due to the huge quantity of stimulus. Thus, it's very important to establish a portfolio of representative stimuli to fit the subject's ability and to properly reduce the number of samples to be evaluated. Generally, *factional factorial design* will be adopted to downsize the size of the stimulus portfolio to a range of numbers that are administrable. The *orthogonal array method* is the most commonly used method in factional factorial design in conjoint analysis.

It is necessary to let all of the attributes and levels have equal emerge frequency because conjoint analysis is used to evaluate the subjects' preferred factor effective value for each attribute level. The best advantage of the *orthogonal array chart* is to decrease the huge number of stimuli to a range of numbers that can be dealt with by subjects. Besides, an *orthogonal array chart* can make all of the levels emerge completely with equal emerge frequency.

2.4 Conjoint Design with Illustrative Style of Icon

Based on the concepts discussed above, four illustrative styles of icon attributes and their corresponding levels were defined, as shown in Table 2. Following the heuristic to use a similar number of attributes and attribute levels as frequently recommended in the relevant literature (Reutterer and Kotzab, 2000), we chose three levels for each attribute and arrived at the following basic utility function for profile evaluation:

$$Yj=\beta 0+\beta 1x1j+\beta 2x2j+\beta 3x3j+\beta 4x4j+ej, \tag{1}$$

where yj represents the evaluation of profile;
$j=1,\ldots,m$ (a set of m=9 stimuli profiles) observed from a specific person;
$i=1,\ldots, n$; $\beta 0$ is a constant term;
$\beta 1,\ldots, \beta 4$ are the model parameters indicating the effect of attribute level variation on the profile evaluation to be estimated.

The indicator variables $x1, j,\ldots, x4$, j represent a set of dummy variables reflecting the effect-coding for the attribute level combination of profile j ($x1$: shadow, $x2$:perspective, $x3$: emboss, $x4$: frame). Finally, ej is an exogenous stochastic nuisance term.

Since we observe m profile evaluations for each of the n represents, input data in an elongated $m\times n$ two-way matrix or a so-called "stacked data" format, and the regression-type model formulation described by Equation (1) can be more compactly rewritten as

$$y = Xb + e, \tag{2}$$

in which $\boldsymbol{y}$ is the column vector containing the profile evaluation values of respondents; the matrix $\boldsymbol{X}$ resembles the (binary) indicator variables as row vectors of the predictors; $\boldsymbol{b}$ represents the column vector of the parameters to be estimated; $\boldsymbol{e}$ again gathers the stochastic disturbances. The remaining task for the conjoint analyst is to fit Equation (1) with the observed profile evaluations collected in the empirical study.

2.5 Neural Networks (NNs)

NNs are non-linear models and are widely used to examine the complex relationship between input variables and output variables (Nelson and Illingworth, 1991). NNs are well suited to formulate the product design process for matching the product form (the input) to the consumer's perception of product image (the output), which is often a black box and cannot be precisely described. Due to their effective learning ability, NNs have been applied successfully in a wide range of fields, using various learning algorithms (Hsu *et al*, 1999; Ishihara *et al*, 1995; Kwok and Smith, 2000; Liu *et al*, 2003; Smith and Gupta, 2000; Smith *et al*, 1996; Wei, 2001). In this study, we used the multilayered feed-forward NNs trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm (Nelson and Illingworth, 1991).

As shown in Figure 2, a typical three-layer network consists of an input layer, an output layer, and one hidden layer, with $\boldsymbol{n}$, $\mathbf{m}$, and $\boldsymbol{p}$ neurons, respectively (indexed by $\mathbf{i}$, $\boldsymbol{j}$, and $\boldsymbol{k}$, respectively) (Tanoue *et al*, 1997). w_{ij} and w_{kj} represent the weights for the connection between neuron $\boldsymbol{i}$ ($\boldsymbol{i}$ = 1; 2; : : : ; $\boldsymbol{n}$) and neuron $\boldsymbol{j}$ ($\boldsymbol{j}$ = 1; 2; : : : ; $\boldsymbol{m}$), and between neuron $\boldsymbol{j}$ ($\boldsymbol{j}$ = 1; 2; : : : ; $\boldsymbol{m}$) and neuron $\boldsymbol{k}$ ($\boldsymbol{k}$ = 1; 2; : : : ; $\boldsymbol{p}$), respectively. In training the network, a set of input patterns or signals, ($\boldsymbol{x}_1$; $\boldsymbol{x}_2$; : : : ; $\boldsymbol{x}_n$), is presented to the network input layer. The network then propagates the inputs from layer to layer until the output layer generates the outputs. This involves the generation of the outputs ($\boldsymbol{y}_j$) of the neurons in the hidden layer as given in (3) and the outputs ($\boldsymbol{y}_k$) of the neurons in the output layer as given in (4):

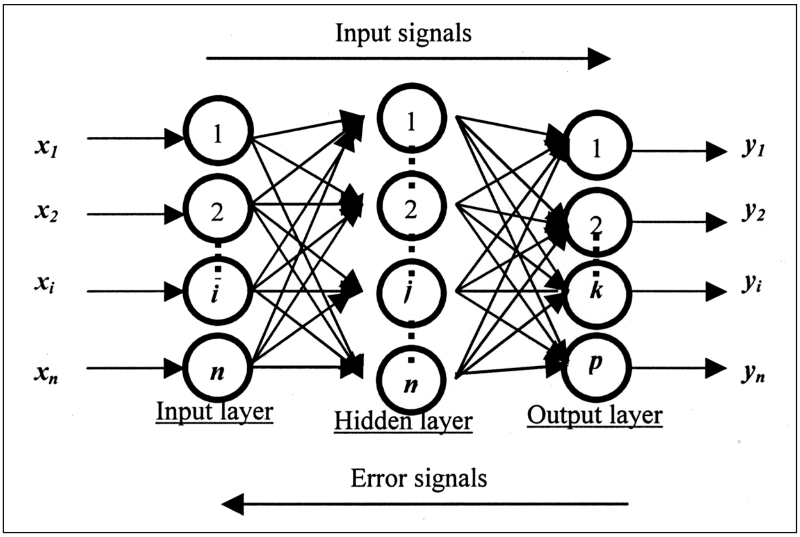

Figure 2: Three-layer feed-forward NN

$$y_j = f\left(\sum_{i=1}^{n} x_i w_{ij} - \theta_i\right), \tag{3}$$

$$y_k = f\left(\sum_{i=1}^{m} x_j w_{jk} - \theta_k\right), \tag{4}$$

Where $f(.)$ is the sigmoid activation function as given in (5), and _j and _k are threshold values.

$$f(X) = \frac{1}{1+e^{-X}} \tag{5}$$

If the outputs (y_k) generated by (4) are different from the target outputs (y_k^*), errors ($e_1; e_2; : : : ; e_p$) are calculated by (6) and then propagated backwards from the output layer to the input layer in order to update the weights for reducing the errors:

$$e_k = y_k^* - y_k. \tag{6}$$

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)

$$\Delta w_{jk} = \alpha y_j \delta_k, \tag{7}$$

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

$$\delta_k = y_k(1-y_k)e_k. \tag{8}$$

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

$$\Delta w_{ij} = \alpha x_i \delta_j, \tag{9}$$

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

$$\delta_j = y_j(1-y_j)\sum_{k=1}^{p} \delta_k w_{jk}. \tag{10}$$

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

3. RESEARCH METHODS AND STEPS METHODOLOGY

In this study, research design consisted of five steps: The first stage, collecting Music Player Software materials and determining the icon samples to be used in the investigations. The second stage, defining the illustrative styles and the design elements of the icons. The third stage, drawing the icon samples after orthogonal design and revising their visual effects. The fourth stage, gathering and screening the words. The fifth stage, designing questionnaires and investigating.

3.1 Extracting Representative Samples of Icon

We collected the icons on the function lists from different brand digital cameras, including Fuji (F401), Konica (KD400Z), Nikon (995), Sony (DSC-P2) and Premiere. The different function icons are codified in Table 1 according to the most commonly used functions, for example, Flash mode,

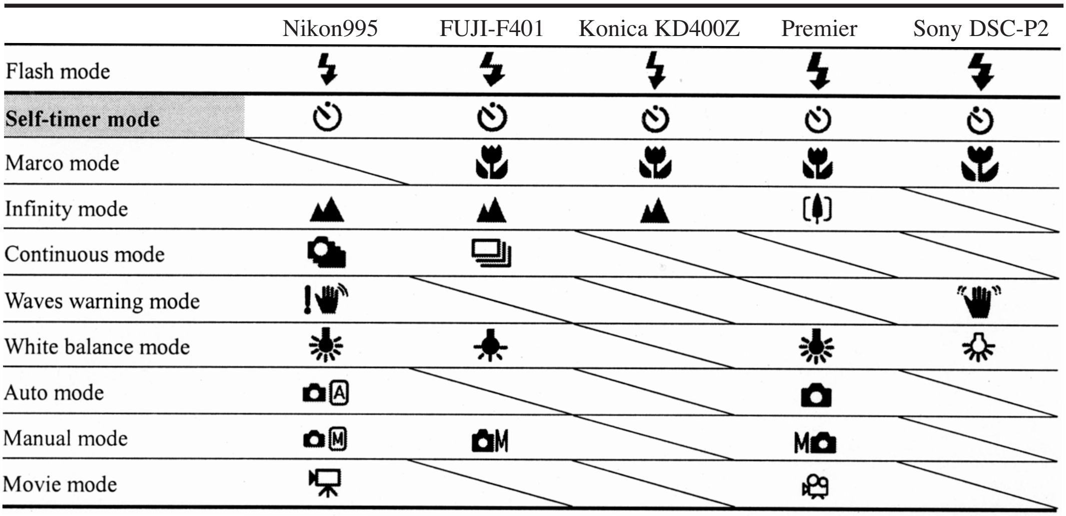

Table 1: The most commonly used function icons of different digital cameras

Self-timer mode, Marco mode, Infinity mode, White balance, etc. Because the icon itself involves the issues of icon recognition to users, the icons we chose were based not only on the data we collected but also on the icons commonly used among different brand cameras. Finally, we picked the icon of *Self-timer mode* as the investigated icon in this study.

3.2 Define the Illustrative Style and Design Elements of the Icon

In accordance with the standard way of picturing the static icon, this study defines the illustrative styles of the picture of the static icon as "*shadow style*", "*perspective style*", "*emboss style*", and "*frame style*" when defining the design condition of the icon, Each illustrative style is divided into three kinds of design element. The definition of illustrative style and designing elements are narrated as Table 2, e.g. the frame style is divided into three kinds including non-frame, square-frame and circular-frame.

3.3 Extracting Representative Samples of Orthogonal Design

According to the definition of icon design conditions, we could combine all the possible portfolios collocated with colours into samples (3×3×3×3×8=648 samples). During the investigating, this may impose a burden on the observers that participate in the test and influence the accuracy of the

Illustration style		Level (Design elements) (1)	(2)	(3)
A	Shadow style	Non-Shadow	Plane-shadow	Gradual-shadow
B	Perspective style	Non-Perspective	Right-perspective	Left-perspective
C	Emboss style	Non-Emboss	Sharp-emboss	Round-emboss
D	Frame style	Non-Frame	Square-frame	Circular-frame

Table 2: Definition of the design condition of the icon

Sample	Code	(A) Shadow style	(B) Perspective style	(C) Emboss style	(D) Frame style
Sample 1	$A_1B_1C_1D_1$	Non	Non	Non	Non
Sample 2	$A_3B_2C_3D_1$	Gradual	Right	Round	Non
Sample 3	$A_3B_3C_1D_2$	Gradual	Left	Non	Square
Sample 4	$A_2B_1C_3D_2$	Plane	Non	Round	Square
Sample 5	$A_2B_3C_2D_1$	Plane	Left	Sharp	Non
Sample 6	$A_2B_2C_1D_3$	Plane	Right	Non	Circular
Sample 7	$A_1B_3C_3D_3$	Non	Left	Round	Circular
Sample 8	$A_3B_1C_2D_3$	Gradual	Non	Sharp	Circular
Sample 9	$A_1B_2C_2D_2$	Non	Right	Sharp	Square

Table 3: Nine icon samples designed according to the experimental layout of L_9 (3^4) orthogonal array

measurement results. Therefore, this study carries on the L_9 (3^4) orthogonal array of the sample according to the definition of the icon design conditions first, before the investigation. Later, under the various kinds of illustrative styles of icon design conditions, we equalize the used numbers of various kinds of illustrative styles. This is the principle to induce constructional conditions of new samples. Moreover, under different presentation forms, the frequency of each kind of design element is averaged, so that we could arrange new samples of each icon. The assignment of orthogonal design of the icons for digital cameras is shown in Table 3.

3.4 Colour Samples

In the preparation of colour samples, we adopted the CIE L*a*b* colour coordinate system because it has relatively more uniform colour spaces than other colour order systems (Ex. Munsell, NCS). Another reason is that the purpose of this study is to estimate future huge numbers of colours using fewer colour numbers and to establish the relationship among icon, colours, and image words. Thus, it's quite important to adopt a more even colour space system. Eight colours, namely red, orange, yellow, yellow-green, green, cyan, blue and purple, were picked from the angles of 0, 45, 90, 135, 180, 225, 270, and 315, respectively. The CIELAB & RGB values of each colour are shown in Table 4.

Colour	L*	a*	b*	C*	h	R	G	B
Red	60.38	72.33	62.51	95.60	40.84	255	0	0
Orange	75.03	35.47	73.04	81.20	64.09	255	153	0
Yellow	95.44	-16.56	85.26	86.85	100.99	255	255	0
Yellow-Green	87.17	-59.76	75.57	96.34	128.34	153	255	0
Green	83.10	-91.08	69.96	114.85	142.47	0	255	0
Cyan	59.60	-6.61	-61.49	61.84	-96.14	0	153	255
Blue	34.65	52.57	-97.65	110.91	-61.70	0	0	255
Purple	47.85	64.86	-75.85	99.80	-49.46	153	0	255

Table 4: CIELAB and RGB value of the 8 colour centre

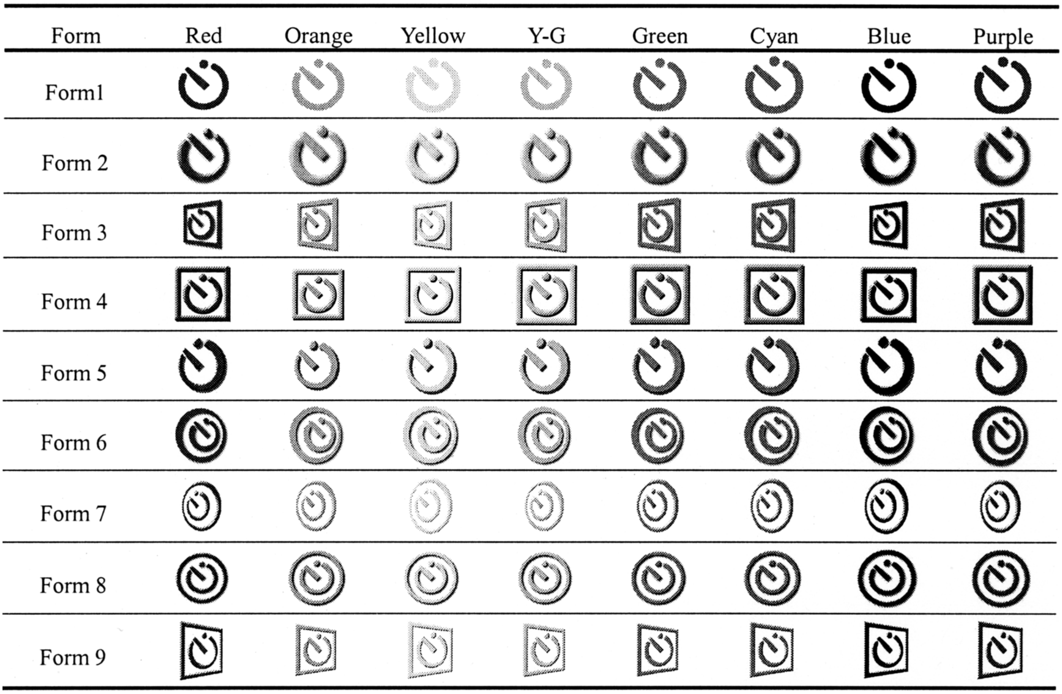

Table 5: Experiment samples

According to the nine representative icons of the orthogonal design mentioned above, each of the icons was displayed in the eight different colours. There were in total 72 icons to evaluate in the experiment. We then generated a new series of icon samples using graphics software. These experimental samples are shown in Table 5.

3.5 Extracting Representative Kansei Words

In selecting Kansei words, we widely collected and coordinated words suitable for expressing the icon images. Through group discussion with 30 professionals who each had more than three years in graphic design, we first sieved out improper words that have close or uncertain meanings for expressing the icon image. Finally, we chose 26 Kansei words suitable for describing the image of icons (Table 6).

150 subjects, consisting of 100 with design backgrounds and the remainder with non-design backgrounds, were invited randomly to carry out icon image evaluation using Kansei words. The subjects were aged from twenty to thirty-five years and all of them had normal vision. They were asked to evaluate the icon samples according to their impressions in terms of 26 Kansei words. In

Order	Repeated	Balanced	Harmonious	Proportion	Gradual	Drowsy	Free
Emphasize	Contrast	Integrate	Symmetrical	Bold	Soft	Neat	Unconstrained
Stable	Lively	Rhythm	Cadence	Simple	Strong	Quiet	Round
Classical	Elegant						

Table 6: Tentative selection of 26 Kansei words

the questionnaire, every sample was allocated to a frame with 85*85 pixels adjusted to fit the visual sight. In the experiment, a 7-point Likert Scale was used to evaluate the personal subjective feelings. On the scale, 1 means that the subject rates a specific sample with the lowest degree of a Kansei word (for example, not elegant at all), 4 means a moderate degree of a specific image (for example, fairly elegant), and 7 represents the highest degree of a specific image word (for example, extremely elegant). In addition, due to the huge data base in the following experiment, we used IIS (Internet Information Service) to collocate Windows XP system to construct the website servers. In order to avoid recording errors, interactive questionnaires were made using ASP (Active Server Page) programming language software so that subjects could answer the questions online and the information they sent be recorded into Access database correctly.

Word	Factor1	Factor2	Factor3	Factor4	Eigenvalue	Contribution degree	Accumulated contribution degree %
Integrate	0.963	0.174	0.153	0.080	12.921	49.69	49.69%
Quiet	0.956	0.066	0.075	-0.022			
Order	0.956	0.002	0.140	0.209			
Rhythm	-0.941	-0.076	0.011	-0.191			
Lively	-0.941	0.255	0.133	0.043			
Harmonious	0.936	0.264	0.228	0.009			
Cadence	-0.933	-0.215	-0.039	-0.189			
Stable	0.919	0.148	0.307	0.089			
Neat	0.906	-0.034	0.351	0.175			
Balanced	0.891	0.231	0.213	0.272			
Proportion	0.836	0.206	0.444	-0.089			
Simple	0.836	-0.235	0.074	-0.440			
Symmetrical	0.836	0.202	0.205	0.436			
Elegant	0.174	0.945	-0.063	0.151	5.145	19.79	69.48%
Gradual	-0.224	0.897	0.273	0.047			
Drowsy	-0.145	0.893	-0.312	-0.029			
Round	0.381	0.832	0.001	-0.003			
Classical	0.585	0.759	-0.041	-0.032			
Soft	0.152	0.724	-0.616	0.024			
Repeated	0.066	0.574	0.543	0.492			
Unconstrained	-0.347	-0.020	0.912	-0.198	5.059	19.46	88.94%
Strong	0.358	-0.207	0.906	-0.003			
Bold	0.409	-0.106	0.894	0.061			
Contrast	0.487	-0.010	0.787	0.296			
Emphasize	0.642	0.184	0.704	-0.033			
Free	-0.642	-0.043	0.110	-0.746	1.587	6.11	95.05%

Table 7: Factor loading matrix after the rotation

To make possible comparison of differences between icon samples, the questionnaire was designed to allow for the evaluation of one question at a time and each sample was rearranged side-by-side. The average grades of all Kansei words on every sample were computed immediately as soon as the survey was completed, and the arithmetic mean of samples was determined through *factor analysis* by *principle component* method. To make sure that the extraction of common factors

	Word	classification 1	classification 2	classification 3	classification 4	Distance from the centre
1	Integrate	0.963	0.174	0.153	0.080	0.1531
2	Quiet	0.956	0.066	0.075	-0.022	0.2243
3	Order	0.956	0.002	0.140	0.209	0.2322
6	Harmonious	0.936	0.264	0.228	0.009	0.1764
8	**stable**	**0.919**	**0.148**	**0.307**	**0.089**	**0.0751**
9	Neat	0.906	-0.034	0.351	0.175	0.2047
10	Balanced	0.891	0.231	0.213	0.272	0.2475
11	Proportion	0.836	0.206	0.444	-0.089	0.2582
12	Simple	0.836	-0.235	0.074	-0.440	0.6395
13	Symmetrical	0.836	0.202	0.205	0.436	0.3918
25	Emphasize	0.642	0.184	0.704	-0.033	0.5150
First classification centre		0.880	0.110	0.263	0.062	
4	**Rhythm**	**-0.941**	**-0.076**	**0.011**	**-0.191**	**0.1316**
5	Lively	-0.941	0.255	0.133	0.043	0.4313
7	Cadence	-0.933	-0.215	-0.039	-0.189	0.2411
26	Free	-0.642	-0.043	0.110	-0.746	0.5283
Second classification centre		-0.864	-0.020	0.054	-0.271	
14	**Elegant**	**0.174**	**0.945**	**-0.063**	**0.151**	**0.1600**
15	Gradual	-0.224	0.897	0.273	0.047	0.4862
16	Drowsy	-0.145	0.893	-0.312	-0.029	0.4294
17	Round	0.381	0.832	0.001	-0.003	0.2622
18	Classical	0.585	0.759	-0.041	-0.032	0.4634
19	Soft	0.152	0.724	-0.616	0.024	0.5947
20	Repeated	0.066	0.574	0.543	0.492	0.7394
Third classification centre		0.141	0.804	-0.031	0.093	
21	Unconstrained	-0.347	-0.020	0.912	-0.198	0.6248
22	Strong	0.358	-0.207	0.906	-0.003	0.1858
23	**Bold**	**0.409**	**-0.106**	**0.894**	**0.061**	**0.1853**
24	Contrast	0.487	-0.010	0.787	0.296	0.3838
Fourth classification centre		0.2267	-0.0856	0.8749	0.0391	

PS: The representative Kansei words of each group are marked with a grey background.

Table 8: The coordinate values of each Kansei word and its Euclidean distance from each centre

can express words more completely, the factor space was rotated by *Varimax method*. After observing the steep chart and the matrix of rotated factors (Table 7), we finally extracted four factors of which the eigenvalues are greater than 1.

The degree of contribution of each factor (the variations of expression) is 49.69%, 19.79%, 19.46%, and 6.11% respectively, and the sum of the degree of accumulated contribution is 95.05% (Table 7). A bigger factor loading of a Kansei word means that specific Kansei word plays a more important role in the component.

In order to select representative Kansei words more carefully, we took the factor loading of these 26 Kansei words in four dimensions as the four-dimension coordinate for each word. We further calculated the distances between each word on the four dimensions using the *Ward Method of Hierarchical Cluster Analysis*, and selected as the representative words those that were the closest to the group centre of each cluster. All the words were divided into four groups according to a cluster analysis tree-form chart and the representative Kansei words we selected were the ones nearest the centre of gravity in each group. Based on the representative words we obtained (Table 8), the following four Kansei words were chosen for further investigation of image characteristic extraction of the images “stable”, “rhythm”, “elegant”, and “bold”.

3.6. Questionnaire Design and Investigation

In this study, we designed the questionnaire to adopt the Semantic Differential Method, abbreviated as SD method. The subjects were asked to conduct the evaluation task according to their personal subjective judgements of the 72 icon samples in four Kansei words, “stable”, “rhythm”, “elegant”, and “bold” on a 7-point Likert Scale. For this stage, forty-four subjects were chosen to participate in the on-line investigation. Each one had to rate a kansei word, a group of colours as well as nine samples on every single page. It meant that there were a total of 32 pages in the investigations (4 Kansei words, 8 colours) and 288 evaluations (32* 9= 288). Before the investigations, the subjects were asked to observe every sample for one minute, which was allocated to an 85*85 pixel frame adjusted to fit the visual size.

Furthermore, we continued the encoding work according to the icon image and design element analysis table, which means representing all items under each category by numbers, such as 1, 2, 3, and 4, etc. As a result, we could decide to which category each sample belonged by contrasting the characteristic of each icon sample and design element. In the analysis, each icon sample consists of a series of 5 numbers. After compiling the average number of each word and the encoding numbers of the 72 samples, the partial contents of 72 selected samples could be obtained (Table 9).

No.	Shadow style	Perspective style	Emboss style	Frame style	Colour	Bold	Rhythm	Stable	Elegant
1	1	1	1	1	1	2.52	3.41	4.41	2.52
2	3	2	3	1	1	3.03	3.31	4.90	3.14
3	3	3	1	2	1	4.00	4.48	4.93	3.41
4	2	1	2	2	1	3.21	4.31	4.31	5.79
5	2	3	2	1	1	3.00	3.90	3.24	3.34
68	2	3	2	1	8	4.23	4.65	4.65	2.97
69	2	2	1	3	8	3.71	4.84	4.03	3.13
70	1	3	3	3	8	3.29	4.48	2.58	5.06
71	3	1	2	3	8	3.45	3.77	5.10	3.35
72	1	2	2	2	8	3.19	4.10	2.77	4.32

Table 9: The coding numbers and image evaluation results for 72 selected samples

4. RESULTS AND DISCUSSION

In this section, we present the results of the conjoint analysis and NN techniques. The experimental results summarized in Tables 3, 5 and 9 are used to answer the research problems.

4.1 Conjoint Analysis

In this section, the *Conjoint Analysis* and *discrete model* were used to analyze the results of the icon design conditions and four Kansei words. Using Kendall's tau grade correlation coefficient, the correlation coefficients with the evaluation value of subjects to four groups of Kansei words are 0.96, 0.97, 0.98, and 0.95 respectively. The statistical significance test reached the significant level ($p<0.05$), which means there is a close relationship among subjects' image evaluations of different icon design conditions. On the other hand, the icon image evaluations of subjects at different design conditions are consistent. Thus, the result of the investigations is quite reliable.

Table 10 shows each illustrative style and design element in every icon design condition, and reports the influences on those four Kansei words. The fact that the five illustrative styles, such as "shadow style", "perspective style", "emboss style", "frame style", and "colour", in each icon design conditions have significant differences in icon image evaluation demonstrates that "colour" is the most influential illustrative style.

design conditions \ kansei word		bold		rhythm		stable		elegant	
Shadow style	Non	18.74	-0.244	13.19	-0.119	20.20	-0.630	19.50	0.029
	Plane		***0.331**		***0.109**		***0.674**		-0.071
	Gradual		-0.087		0.011		-0.043		***0.042**
Perspective style	Non	17.90	-0.273	23.69	-0.642	23.53	***0.935**	13.04	-0.049
	Right		***0.145**		0.301		-0.361		***0.149**
	Left		0.128		***0.341**		-0.575		-0.099
Emboss style	Non	12.86	-0.101	13.59	-0.089	12.77	-0.185	23.33	-0.384
	Sharp		***0.124**		***0.115**		***0.108**		-0.446
	Round		-0.023		-0.026		0.077		***0.830**
Frame style	Non	18.68	***0.191**	20.30	-0.019	15.66	***0.367**	11.80	***0.043**
	Square		-0.260		-0.334		-0.396		0.010
	Circular		0.069		***0.352**		0.029		-0.052
Colour	Blue	**31.83**	0.068	**29.23**	-0.009	**27.84**	0.216	**32.34**	-0.178
	Cyan		-0.243		0.099		0.052		0.155
	Green		0.033		-0.085		-0.176		-0.113
	Orange		-0.058		-0.141		0.193		-0.019
	Purple		0.126		0.041		0.171		-0.027
	Red		***0.497**		***0.180**		***0.224**		-0.398
	Yellow		-0.205		-0.110		-0.489		0.236
	Yellowish green		-0.218		0.024		-0.191		***0.344**
Constant			3.661		3.898		4.051		3.403
Pearson' s R			0.963		0.968		0.984		0.947
Kendall' s (tau)			0.826		0.847		0.891		.725
Significance			*0.000		*0.000		*0.000		*0.000

Table 10: Results of conjoint analysis

illustrative style / Kansei word	Shadow style	Perspective style	Emboss style	Frame style	Colour
bold	Plane	Right	Sharp	Non	Red
rhythm	Plane	Left	Sharp	Circular	Red
stable	Plane	Non	Sharp	Non	Red
elegant	Gradual	Right	Round	Non	Yellowish Green

Table 11: The results of postive icon image with conjoint analysis method

The experimental results were analyzed by conjoint analysis. Table 11 reflects the allocation of colour and design elements at each illustrative style for each Kansei word. More detailed explanations are listed below:

In order to reach stronger "bold" image, people should adopt "plane-shadow", "red colour", "right-part-perspective", "sharp-emboss", and "non-frame". In order to reach stronger "rhythm" image, people should adopt "plane-shadow", "left-part-perspective", "sharp-emboss", and "circular-frame", and "red colour". In order to reach stronger "stable" image, people should adopt "non-perspective", "plane-shadow", "non-emboss", "non-frame", and "orange colour". In order to reach a stronger "elegant" image, people should adopt "sharp-emboss", "yellow-green colour", "right-part-perspective", "circle-frame", and "gradual shadow".

4.2 NN Analysis

In this section, the effective technique for determining the best combination of colour and design elements for matching a desirable icon image is discussed through NN analysis with different computing rules.

4.2.1 Building the NN Analysis

For eight colours and four illustrative styles (each has three design elements), 20 input neurons are needed in NN analysis. The explanation of input layer, hidden layer and output layer is given in Table 2. For the NN analysis, if an icon has a particular design element, the value of the corresponding input neuron is 1; otherwise the value is 0. The output neurons of the model are the bold, rhythm, stable and elegant values ranging between 1 and 7, as specified in the experimental study. In this study, we apply the following four most widely used rules (Nelson and Illingworth, 1991) to determine the number of hidden neurons in the single hidden layer for both models:

(HN1) (The number of input neurons + the number of output neurons)/2, (11)
(HN2) (The number of input neurons * the number of output neurons)^0.5, (12)
(HN3) (The number of input neurons + the number of output neurons), (13)
(HN4) (The number of input neurons + the number of output neurons)*2, (14)

To distinguish between the NN analyses by different rules, both models are associated with the rule used, such as -HN1, -HN2, -HN3, -HN4, as shown in Table 12. Table 12 shows the neurons of the NN analysis, including the input layer, the hidden layer, and the output layer.

4.2.2 Comparing the Results of the Different Hidden Layers

The 64 samples in the training set (given in Table 9) were used to train the NN analysis. The model learned fast with the root mean square (RMS) error decreasing significantly when the model was

The NN analysis	Input layer: 20 neurons (8 colour s + 12 design elements).
	Output layer: 4 neuron for the "bold", "rhythm", "stable", and "elegant" value.
-HN1	Hidden layer: 12 neurons, (20 + 4)/2 = 12.
-HN2	Hidden layer: 9 neurons, (20 × 4)^0.5 = 8.94 = 9.
-HN3	Hidden layer: 24 neurons, (20 + 4) = 24.
-HN4	Hidden layer: 48 neurons, (20 + 4)*2 = 48.

Table 12: Neurons of the NN analysis

Number of epochs	NN -HN1	NN -HN2	NN -HN3	NN -HN4
1000	0.0563	0.0631	0.0552	0.0515
2000	0.0456	0.0454	0.0448	0.0444
3000	0.0431	0.043	0.0431	0.0425
4000	0.0422	0.042	0.042	0.0436
5000	0.0416	0.0411	0.0426	0.0428
6000	0.0412	0.041	0.0418	0.0423
7000	0.0403	0.0406	0.0411	0.0423
8000	0.0403	0.04	0.0416	0.043
9000	0.0402	0.0396	0.0409	0.0421
10000	0.0394	0.0395	0.0406	0.0423
11000	0.0385	0.0383	0.0395	0.0406
12000	0.0385	0.0381	0.0392	0.0404
13000	0.0383	0.038	0.0392	0.0398*
14000	0.0382	0.0378	0.0392	0.0403
15000	0.038*	0.0377*	0.039*	0.04

Table 13: RMS errors of the NN analysis for the training set

trained for about 4000-5000 epochs. For example, the RMS error of the NN-HN1 model decreased from 0.3768 to 0.0984 as the training proceeded for about 4300 epochs. For training epochs between 4300 and 5000, the error changed slightly within a range of 0.0712 to 0.1010. In a sense, this could be regarded as having converged. To find the best training result, we continued the training process up to 15,000 epochs for all models. Table 13 shows some representative results, where the lowest RMS error of each model using a given hidden neuron number is asterisked.

As shown in Table 13, the RMS error of the NN analysis using the HN2 rule is the lowest (0.0377), as compared to the other three rules. Like the NN analysis, each simplified NN analysis uses the four rules (HN1, HN2, HN3, and HN4), respectively, for determining the hidden neurons. This result is in line with the general understanding that the more the input neurons, the better the training result.

5. PERFORMANCE EVALUATION OF ANALYSIS

To evaluate the performance of different analyses in this study in terms of their prediction ability in determining the best design combination of colour and design elements for matching given the bold, rhythm, stable and elegant images, the eight samples in the test set identified in Table 4 are used. The 44 subjects are involved in the process, using the *semantic differential method* (Osgood and Suci, 1957) with a 7-point scale (1-7). For example, the second row of Table 14 shows the

	Icon no.								RMS errors
	2	12	22	32	42	52	62	72	
Evaluated bold value	4.03	3.39	4.16	4.71	4.39	3.97	3.16	3.19	–
CA model	3.931	3.206	4.092	3.928	4.263	4.287	3.288	3.158	0.045
NN -HN1	4.217	3.361	3.930	4.653	4.549	4.088	3.505	3.312	0.026
NN -HN2	4.227	3.321	3.854	4.664	4.538	4.152	3.464	3.284	0.027
NN -HN3	4.185	3.372	3.876	4.620	4.500	4.124	3.479	3.291	0.025
NN -HN4	4.208	3.377	3.916	4.641	4.535	4.134	3.505	3.340	0.026
Evaluated rhythm value	4.32	4.13	3.13	4.61	4.74	4.77	3.55	4.1	—
CA model	4.143	3.800	3.807	3.845	4.632	4.483	3.996	3.704	0.064
NN -HN1	4.360	4.307	3.234	4.412	4.801	4.581	3.646	3.992	0.019
NN -HN2	4.379	4.222	3.199	4.432	4.769	4.662	3.634	3.964	0.014
NN -HN3	4.345	4.275	3.260	4.378	4.760	4.575	3.645	3.961	0.020
NN -HN4	4.331	4.270	3.224	4.382	4.758	4.525	3.636	3.964	0.020
Evaluated stable value	4.03	3.13	5.19	4.81	4.39	3.32	4.52	2.77	—
CA model	3.944	3.953	4.147	5.341	4.259	4.191	3.464	2.715	0.100
NN -HN1	4.352	2.897	5.101	5.025	4.461	2.952	4.600	2.640	0.030
NN -HN2	4.398	2.941	5.131	5.078	4.499	2.938	4.560	2.675	0.032
NN -HN3	4.419	2.955	5.133	5.052	4.456	2.932	4.632	2.678	0.032
NN -HN4	4.421	2.891	5.115	5.021	4.455	2.971	4.602	2.685	0.031
Evaluated elegant value	4.39	3.65	2.65	2.42	3.45	3.81	3.06	4.32	—
CA model	4.168	3.098	3.365	2.814	3.574	2.815	3.575	3.420	0.088
NN -HN1	4.404	3.166	2.653	2.677	2.881	4.138	3.187	3.526	0.059
NN -HN2	4.351	3.160	2.671	2.615	2.828	4.040	3.203	3.419	0.062
NN -HN3	4.357	3.075	2.657	2.679	2.893	4.036	3.135	3.481	0.061
NN -HN4	4.363	3.144	2.682	2.710	2.907	4.088	3.189	3.510	0.059

Table 14: Predicted values and RMS of four Kansei words with CA and NN analysis for the test set

average values of bold image at the eight test samples evaluated by the 44 subjects, which are used as a base of comparison for evaluating the performance. With the eight test samples as the input, Table 14 shows all the corresponding image values predicted by using the conjoint analysis and NN analysis with different hidden layers, respectively.

Table 14 shows that RMSs of all the NN-based models and CA models are very low, suggesting that the NN modes and CA are better techniques for answering the research questions identified in this study.

To examine whether the performance of the NN-based and CA models in Table14 differed significantly, we performed the statistics test on all the modes. Table 15 shows the result of the multiple comparisons by using the least significant difference (LSD) test. In Table 15, the asterisk indicates that the performance of the corresponding pair of models differs significantly at the 0.05 level. The result compared afterwards shows that there exists no significant difference between evaluated results vs. CA and evaluated results vs. an NN-based model. It demonstrates that CA and NN analysis work equally well in predicting the performance.

Multiple comparisons	Mean difference	p value	95% confidence interval	
			Lower bound	Upper bound
Evaluated bold value vs. CA model	0.106	0.261	0.688	-0.422
vs. -NN1 model	-0.077	0.261	0.771	-0.604
vs. -NN2 model	-0.063	0.261	0.811	-0.591
vs. -NN3 model	-0.056	0.261	0.832	-0.584
vs. -NN4 model	-0.082	0.261	0.756	-0.609
Evaluated rhythm value vs. CA model	0.118	0.251	0.642	-0.388
vs. -NN1 model	0.002	0.251	0.992	-0.503
vs. -NN2 model	0.011	0.251	0.965	-0.494
vs. -NN3 model	0.019	0.251	0.940	-0.487
vs. -NN4 model	0.032	0.251	0.898	-0.473
Evaluated stable value vs. CA model	0.018	0.473	0.969	-0.936
vs. -NN1 model	0.017	0.473	0.972	-0.938
vs. -NN2 model	-0.007	0.473	0.988	-0.962
vs. -NN3 model	-0.012	0.473	0.980	-0.967
vs. -NN4 model	0.000	0.473	1.000	-0.954
Evaluated elegant value vs. CA model	0.115	0.311	0.713	-0.513
vs. -NN1 model	0.140	0.311	0.656	-0.488
vs. -NN2 model	0.183	0.311	0.560	-0.445
vs. -NN3 model	0.180	0.311	0.567	-0.448
vs. -NN4 model	0.145	0.311	0.645	-0.484

Table 15: Statistical significance test of the performance of NN and CA models on the test set

6. CONCLUSION

According to the definition of the design condition of the icons, this study used the Orthogonal Design of the icon sample and collocated four evaluated indexes (Kansei words) to examine questionnaires, and used the CA and NNs analysis methods which were expected to find out the top-seeded expression-form-setting of icon design from the results of icon image evaluated questionnaires. From the analysis results, the following conclusions could be made:

1. Four types of illustration style of the icon design conditions are identified, namely “shadow style”, “perspective style”, “emboss style” and “frame style”. For each of them, three different form treatments are specified. The positive bold, rhythm, stability, and elegant icon images could be attained by the different illustration styles and colours. Our classification of the illustration styles could serve as a reference for icon designers.
2. In the presentation of icon images, it is very important to combine different colours and design elements in the icon design.
3. We tried to analyze our data by linear and nonlinear methods, and found that CA and NNs both fall into an acceptable range of the perspective ability.
4. In this study, we applied the four most widely-used rules to determine the number of hidden neurons in the single hidden layer for both models. There is no significant difference between the analytic abilities in this study.
5. The approach to icon image evaluation addressed in this study can be applied to related industries where icons are needed such as graphic design and web design, and help designers to choose the optimum illustrative style of icon.

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