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Research Article

Multisensory Design of Electric Shavers Based on Kansei Engineering and Artificial Neural Networks

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The market scale of electric shavers in China has reached ¥ 26.3 billion in 2021. Consumers currently place an increasing emphasis on the Kansei image conveyed by products rather than just concerning with functional satisfaction. To meet consumers' expectations, the emotional message conveyed by product design is essential under multisensory channels. This research first collected 230 electric shavers samples and 135 pairs of consumers' Kansei words, then reduced them into 34 representative samples using multidimensional scale and clustering analysis, with 4 groups of representative Kansei words selected via the expert group. Moreover, consumers' Kansei images were evaluated via questionnaire using the semantic differential scales, with 416 valid samples acquired in total. Meanwhile, design elements of the samples (including item and category) were classified by ways of morphological analysis and audio software. At last, the prediction models of the electric shavers were established between the overall design elements and user's Kansei evaluation under the multisensory channel of visual model and auditory audio taking advantage of Quantification Theory Type I , back propagation neural network, and genetic algorithm-based BPNN. The proposed models can provide defined design indexes and references in multisensory design, facilitating designers to design in a logical and scientific manner rather than designing as per experience.

1. Introduction

In 2021, the market scale of electric shaver in China has reached 26.3 billion [1]. With the social development and increasing demand, product and structural functions are no longer the only two factors affecting the consumers' behaviors. Now, consumers need to consider more when distinguishing products in the market. Therefore, in a market tailored to emotional and personalized needs, the emotional imagery delivered by the design has become a key factor for improving the competitiveness of the products in the market. As an important method to study the emotional needs of products, Kansei engineering adopts the semantic differential (SD) method to qualify the users' Kansei imagery and translates it into design indicators for innovative design [2]. The previous researches dedicated to the modeling of Kansei engineering mainly used Quantification Theory Type I (QTTI) to establish the prediction model. In the research on car modeling, Lai et al. built the relationship between design features and users' Kansei scaling based on QTTI and proved that different electric vehicle styling can cause different emotional evaluation of consumers [3]. Hu et al. discussed how the design of medical instruments and interfaces helped develop hypertension instruments and interfaces more suitable for the elderly using QTTI multiple linear regression analysis [4]. With the development of computer technology, in the research of artificial neural networks applied to product innovation and design, Long Wu used a computer mouse modeling design as an example to construct a Kansei model between modeling design elements and Kansei imagery through artificial neural networks, which provides a new design approach oriented to users' emotional needs [5]. Wu et al. constructed a Kansei prediction model by quantitative analysis of Goblet containers based on an artificial neural network, which provides a Kansei scaling about product design features to guide an optimized design of product tailored for the user's imageries [6].

In addition to visual modeling, auditory information is another important aspect in product emotional research. According to multisensory design theory, when interacting with products, users receive not only visual information but also auditory information [7]. Based on the research of audio, the semantic differential scales was adopted by Liu et al. to study how to use it to collect Kansei scales of cues to optimize the wheelchair sound and assist people with disabilities to better operate their wheelchairs, which proved the feasibility of applying Kansei engineering in the field of sound [8]. Muramatsu et al. measured and quantified environmental sounds to build a neural network model and developed a 3D technology-based sound walking guidance system for the visually impaired [9].

Although certain emotional needs of users can be satisfied by the traditional research on the modeling or sound of Kansei engineering alone, the modeling and sound produced in the use of products, such as vacuum cleaners, electric shavers, and the aforementioned wheelchairs for people with disabilities, all affect the emotional imagery of users simultaneously. Therefore, the emotional needs of users can be better met by exploring the Kansei imagery conveyed by modeling and sound from a multisensory perspective [7]. In this research, the prediction models of user's Kansei imagery are established based on Kansei engineering and artificial neural networks through linear and nonlinear methods so that a better prediction model is developed for guiding multisensory optimization of product design by comparing the linear and nonlinear models.

2. Literature Review

2.1. Kansei Engineering and Quantification Theory Type I. The main theory for quantitative analysis of users' emotional needs and innovative design research is Kansei engineering [2] proposed by Professor Mitsuo Nagamachi in Japan. Kansei engineering is aimed to transform product design elements and quantified Kansei imageries into design parameters to facilitate design. As a common method for regression analysis and linear correlation models in Kansei engineering, design elements in QTTI are used as multivariate dependent variables for mapping user's Kansei imageries to form multiple linear regression equations and is now widely used in various fields [10–13].

In the research of product modeling, representative samples of electric mobility scooters are selected by Suparmadi using the focus group method and a questionnaire survey is conducted on consumers combined with Kansei words to verify that different types of consumers have different preferences for product modeling. However, representative samples and sample classification used in that research were only determined by experts themselves, so the results were lack of objectivity [11]. In the research of automotive dashboard, the KJ method was adopted to select the representative samples and morphological analysis was adopted to deconstruct design elements to determine the optimal design solution, but further quantitative analysis should be conducted to establish a design prediction model to provide more data for a better design solution and provide clear design indicators for subsequent design applications [12]. In the research of sunglasses, users' Kansei scaling was collected through the semantic difference method by Ngip, and then a prediction model between design elements and Kansei scaling was further formed with QTTI to provide clear design indicators for developing sunglasses [13]. However, despite of the quantitative analysis for prediction model, the limited number of respondents involved in the questionnaire (only 75) lead to the inaccuracy of its prediction model. Based on the aforementioned Kansei engineering literature, it can be found that those research methodology they used has methodological nonobjectivity, unscientific classification, and insufficient sampling number.

Therefore, product modeling and sound have been combined in this research for Kansei engineering, and the samples are classified objectively through multidimensional scale method and clustering analysis method to overcome the shortcomings of previous studies. At the same time, the product is deconstructed according to the morphological analysis method. The different design elements are named as "Items," and the different categories under each item are called "Categories," and the questionnaires are fully collected and then the prediction model is built based on the linear regression analysis of QTTI, so as to develop the multi-sensory design research of electric shavers.

2.2. Back Propagation Neural Network. The back propagation neural network (BPNN) was developed by Gallant in 1993 [14]. The main features of BPNN are their ability to simulate the self-learning and organisational capabilities of the human brain, to process incomplete data and to solve complex and ill-defined problems. The basic computational unit of a neural network is referred to as nodes, and nodes are connected in three kinds of layers: input layer, output layer, and hidden layer. The input layer is used to input learning information, the output layer to display results and the hidden layer to process data relationships nonlinearly [15]. In Kansei engineering, the BPNN is used to determine the relationships between product design elements (Items + Categories) and consumer sentiment evaluations, in order to make Kansei predictions.

A few researches have illustrated the application of BPNN in the field of product design. Gao used BPNN to analyse users' expectations of watch modeling and established a predictive model between modelling elements and users' emotional responses, providing a better design reference and indicator for innovative design watch modelling [16]. Zhu and Chen established a correlation model for home service robot modeling solutions based on BPNN, which provides a new design approach for future modeling design of related products to turn towards consumer emotional needs [17]. Once trained, BPNN can perform predictions and generalizations at high speeds. Compared with QTTI, BPNN is modelled with a nonlinear architecture and gradient descent, offering high compatibility and operational convenience. Ding et al. combines QTTI and BPNN in a colour matching study of exercise bikes, revealing the differences between linear and nonlinear methods and giving logical colour matching recommendations [18]. Özcan et al. uses both QTTI and BPNN to build a product design database and proposes a decision-making system based on technique for order preference by similarity to an ideal solution (TOPSIS) and grey relational analysis to assist design decisions [19].

Therefore, this research incorporates the BPNN to model the predictive relationship between design elements and consumer Kansei evaluation values of electric shavers and compares the predictive accuracy with the QTTI linear model.

2.3. Genetic Algorithm-Based BPNN. Genetic algorithm-based BPNN (GA-BPNN) is a stochastic search algorithm and optimization technique that mimics nature's law of "survival of the fittest" evolution. By creating "artificial genetic systems" through gene selection, crossover, mutation operations, GA has a strong predictive approach to large scale and diverse complex problems [20]. The genetic algorithm aggregates all solutions into a genetic domain and searches for the optimal solution by gene swapping rather than searching randomly for single points. There are three basic operational steps in GA: selection, crossover, and mutation. Briefly, in the selection stage, the algorithm first generates a random first-generation chromosome set, called "The candidate solution" for a given scenario. This is followed by an evaluation of the fitness function to determine the probability of each chromosome participating in the inheritance. In the crossover stage, each pair of suitable chromosomes undergoes an exchange of genes to generate the next generation of a superior solution. In the mutation stage, new chromosomes are created by locally adding fresh genes, guaranteeing genetic diversity and validity. Repeated several times, GA ensures that the programme is upgraded in an optimal direction until the desired standard is reached.

Optimisation at a lower cost gives GA the advantage of (1) high compatibility in dealing with complex problems. (2) High accuracy in generating predictions. (3) Efficient exploitation of potential solutions. Adnan developed a hybrid approach based on GA and convolutional neural network (CNN) for natural language processing (NLP) of sentiment discourse, illustrating that GA is superior to traditional CNN in terms of iterative efficiency and compatibility [21]. Yeh used Hybrid GA-based artificial neural networks (ANN) to construct a sports shoes styling-user emotional response prediction model. It was verified that the GA-based ANN has better prediction accuracy in modeling compared to the traditional ANN [22]. Akgül et al.'s application of fuzzy association rules and GA to transform the emotional needs of a cradle chair into design elements demonstrates that GA can assist in exploring superior design solutions [23]. Furthermore, applying BPNN, GRNN, GA-BPNN, and QTTI simultaneously to the construction of imagery models for product sound, the results of the research indicate that GA-BPNN is less cost-effective and time-consuming compared to traditional algorithms in the field of product sound [24].

Hence, this research then uses GA to optimise the search traversal and convergence capabilities of BPNN to build nonlinear prediction model for the modelling + sound elements, in order to better understand the reliability and accuracy of Kansei prediction between different models in the multisensory field.

2.4. Multisensory Design. As a design strategy proposed by Özcan et al. [19], Multisensory design is aimed to explore how multiple senses of products and services interact with each other and influence the user's Kansei imagery. In his research, the detail of products in conveying unisensory versus multisensory imagery were compared and analyzed by Schifferstein to confirm that Kansei imagery can be enhanced or weakened in different sensory associations. For example, car engine sound helps create a sense of security [25] and quality sound of hairdryer enhances power perception [26]. Past research has demonstrated that humans can judge the imagery conveyed by a product through multiple channels of senses simultaneously, because human senses can support each other through synesthesia processes [27]. Therefore, innovative design of products should take into account multiple sensory channels to ensure consistency and integrity in the multiple communication of imagery.

With high market value in the field of personal care appliances, electric shavers have been deeply explored and studied by scholars around the world. In the functional research, ion beam assisted deposition (IBAD) is adopted to enhance the corrosion resistance of electric shaver blade and extend the life of products [28]. Izumi and Sawaguchi used TRIZ theory to optimize the function of electric shaver. He enhanced the flexibility of the blade head, and adopted information integration technology to help companies quickly design new products [29]. Rietzler et al. proposed a method to improve user's comfort by striking the balance between the head temperature and shaving efficiency based on a comparative analysis of different head structures [30].

The traditional research on electric shavers focused on functional optimization and enhancement. When the production technology is improving and becomes mature, more accurate Kansei imagery can better enhance market competitiveness. However, the previous studies failed to take product modeling and sound into consideration at the same time. Therefore, this research will use the QTTI linear and artificial neural network nonlinear methods to construct the correlation model of product visual modeling, auditory audio, and user's Kansei evaluation, and explore the multisensory design of products in a qualitative and quantitative way. So that the design parameters of the optimal model are applied to the innovative design instruction of products.

3. Methodology

In this research, the quantitative and qualitative analysis of electric shaver design was carried out by combining QTTI, BPNN, and GA-BPNN through Kansei engineering. The specific research can be divided into the following aspects (as shown in Figure 1): (I). Representative samples are selected through multidimensional scale and clustering analysis. (II) Representative Kansei words are chosen by focus group method. (III) Items and categories are deconstructed based on product design elements. (IV) The prediction models are built based on QTTI, BPNN, and GA-BPNN. (V) The accuracy of the three prediction models were compared and analyzed so as to select the optimal prediction model.

3.1. Selection of Representative Samples. Firstly, a total of 230 electric shaver samples were obtained by collecting samples extensively from e-commerce platforms and excluding imageries with too complicated backgrounds, as shown in Figure 2.

After the second round of screening (excluding those with high similarity), 80 samples were obtained. For the purpose of eliminating the influence of colour on the subjective preference, Grey-scaling was adopted for samples. In addition, the focus group method was used, 25 graduate students in design and industrial design experts experienced in relevant product design were invited to classify the 80 samples according to the similarity of the samples. The samples were divided into 12~19 groups, and then coded into 80×80 dissimilarity matrix. Then, the six-dimensional coordinate values of each sample were obtained by multidimensional scale analysis with SPSS 23.0 software. The pressure coefficient is 0.04334, RSQ = 0.97915. Finally, the cluster tree of 17 groups of samples was obtained through clustering analysis and Wald method, as shown in Figure 3.

Samples in 17 groups were voted by 5 experts with a background of product design for safeguarding the effectiveness and accuracy of the prediction model in the subsequent studies that shall deconstruct design elements, carry out semantic differential scales questionnaire as well as establish linear and non-linear prediction models for samples. After that, the 2 samples with the greatest number of votes in each group were selected from each group as representative samples. More than that, 1 sample was selected from each of the 4 groups as verification samples [31]. Hence, 34 representative samples can be acquired, as shown in Figure 4.

3.2. Screening of Representative Words. 135 Kansei words about the modeling and sound of electric shavers were collected from literature, journals, users' comment area of e-commerce platform and other channels. After the first round of screening and selection, 40 Kansei words are obtained by eliminating the words with unclear meaning and ambiguity. In order to reduce the load of respondents in the follow-up research, another 30 experts and master's students were invited from industrial design to evaluate the suitability of 40 groups of Kansei words provided (using five-point Likert scale) and finally complete the selection of Kansei words, as shown in Figure 5.

When ranking the Kansei words based on values, four words have the highest values of over 4.5, and the standard deviations of these four words are all less than 1, which are: avant-garde, simple, tough, and advanced. Then, the antonyms are adopted to form four groups of Kansei words: "Traditional/Fashion-forward," "Soft/Harder-edged," "Cheap/Premium," and "Sophisticated/Minimalistic."

3.3. Deconstruction and Classification of Design Elements. The design elements of the electric shaver samples were analyzed based on the morphological analysis method and ArtmeiS 13.6 software. Finally, the design elements were divided into five modeling items (head, neck, handle, switch, and switch activation) and two sound items (tonality, and sound quality). Figure 6 illustrates the modeling differences of heads, necks, and handles.

Concerning modeling items, the ratio of neck shape (head-to-neck ratio/P_1) is the head width ($b1$)/neck width ($b2$). According to the P_1 distribution of samples shown in Figure 7(a), the neck models can be divided into "narrow neck," "average neck," and "broad neck." When the ratio between the neck length and head length is less than 3%, it is classified as "neckless." The streamlined handle model (slenderness ratio/P_2) means the maximum width of the handle ($b3$)/handle length ($b4$). The distribution of sample P_2 is shown in Figure 7(b). According to Figure 7(b), the streamlined handles can be divided into "narrow," "average," and "broad streamlined." The cylindrical handle (slender ratio/P_3) is the diameter of the cylinder/the length of the handle. There are only a small number of samples (7 pieces) with the cylindrical handle, so they can be only divided into "long cylindrical" and "short cylindrical" ones.

In the sounds items, sounds are sampled by HEADREC equipment and ArtmeiS 13.6 software is adopted for the tonality measurements of 34 samples, as shown in the Figure 8. Ch1 T denotes the tonality parameter collected in the left ear of the device, and Ch2 T denotes the tonality parameter collected in the right ear of the device. Then, the average of the two parameters collected from the left and right ears are taken [32]. Tonality mainly describes the subjective reflection of sound frequencies by the respondents and different frequencies can bring different imageries to the respondents. The lower the tonality of the sound, the thicker it is perceived to be, and vice versa. The sound quality reflects the participants' perceptual imageries about the overall sound [33]. A focus group of five experts with good voice perception are invited to categorize the 34 samples as "Low," "Medium," and "High." In ArtmeiS 13.6 software, Hanning window function is more balanced than Hamming window in all aspects of sound detection, so it can provide more accurate results, spectrograms show that shaver sounds are quite stationary, some of these sound locations are very close, especially in the high frequency range, and some are more dispersed. So more closer location and higher A-weighted sound pressure level will result in powerful sound imagery, and vice versa [34, 35]. In this research, sound quality items are mainly categorized as "stable and powerful" and "fluctuating and soft," as shown in Figure 8 and Table 1.

Therefore, based on the analysis of product design elements, 34 electric shavers can be divided into a total of 7 items and 30 categories of design elements, as shown in Table 1.

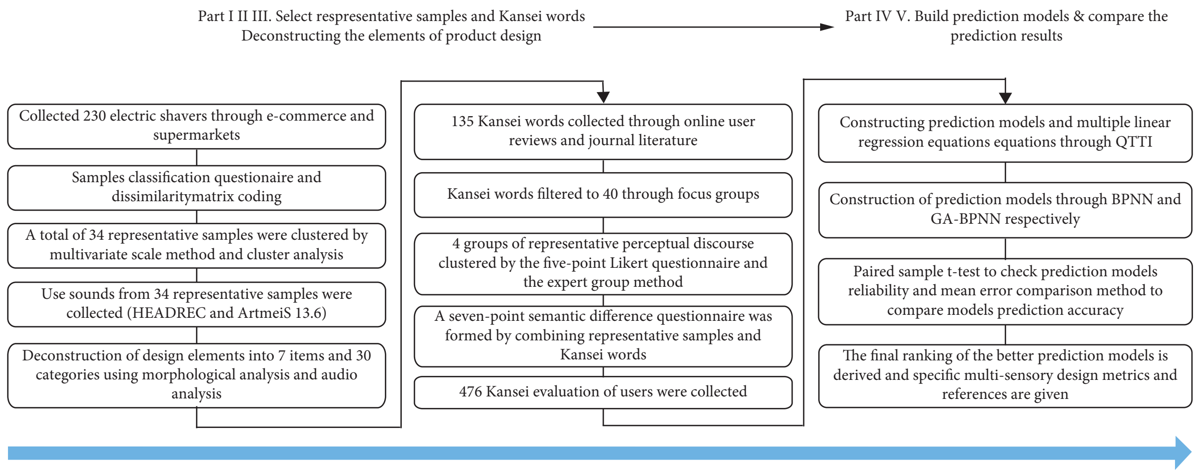


Figure 1: Research flow chart.

Figure 2: Sample of 230 electric shavers.

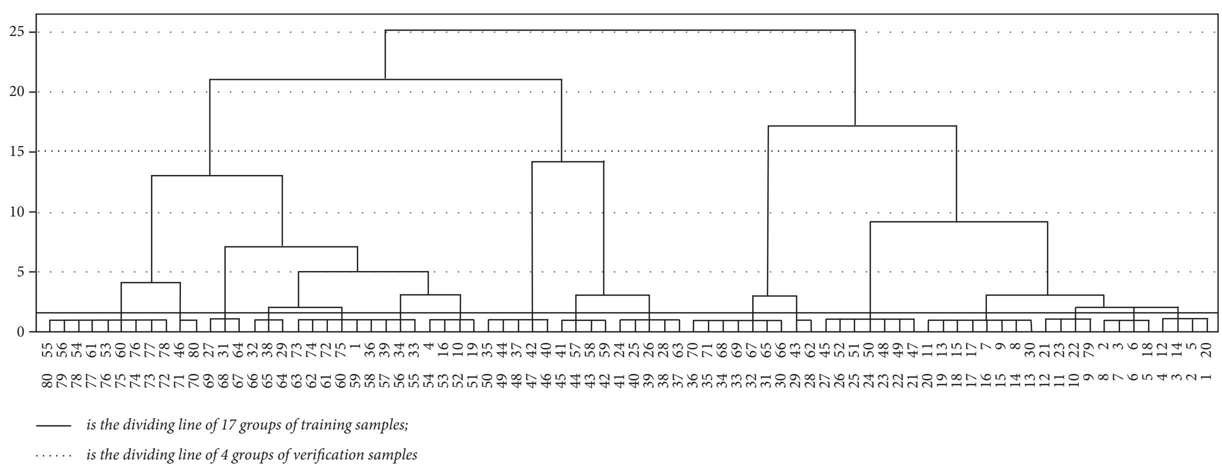


Figure 3: Clustering analysis map.

Figure 4: Representative samples.

4. Results and Discussion

4.1. The Establishment of Prediction Model Based on QTTI. Combining 34 sample pictures with 4 groups of Kansei words, this research adopts 7-point Likert questionnaire. The respondents made Kansei evaluation on different Kansei words according to the modeling and sound of the samples. All 478 questionnaires are distributed to males in this research. 62 invalid questionnaires are excluded, and a total of 416 valid questionnaires are analyzed based on QTTI, as shown in Table 2.

According to the table, the coefficient of determination "Traditional/Fashion-forward" R^2 is 0.868, so it means that the prediction equation can explain the change of 86.8% of the dependent variable. The coefficients of determination of the other three groups of Kansei words are 91.7%, 87.2%, and 87.9% respectively, demonstrating good fitting results.

4.2. Establishment of Multiple Linear Regression Equation. QTTI constructs a qualitative and quantitative multiple linear regression equation using design elements (30

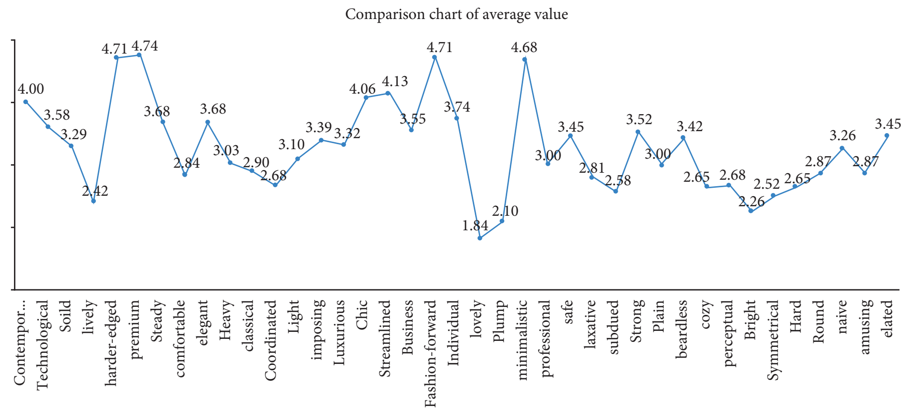


FIGURE 5: Comparison of average values of Kansei words.

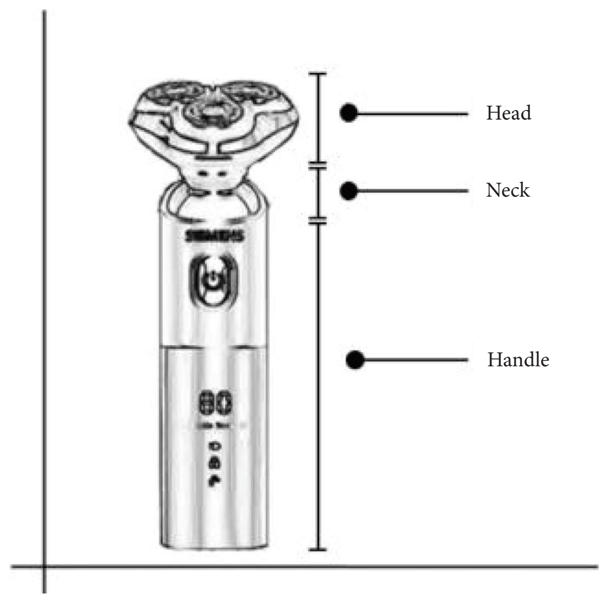
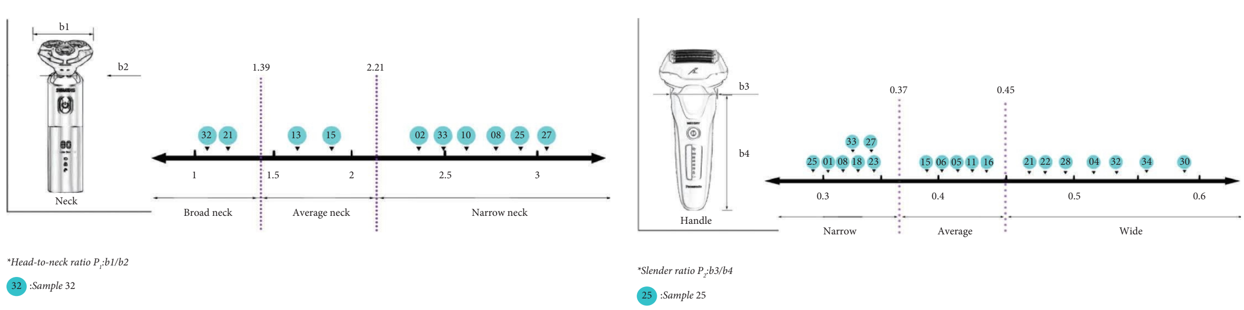


FIGURE 6: Schematic diagram of modelling parts.



(a) (b)

FIGURE 7: Distribution of (a) the head to neck ratio of the blade and (b) the slender ratio of the handle.

categories) as independent variables and user's Kansei evaluation values (416 questionnaires) as dependent variables, e.g., a_{ij} means the jth category under the ith item of the product as a coefficient of this equation, X_{11}, X_{12}, X_{13}, . . ., X_{71}, X_{72} means the different categories of the equation, and ε_κ is the constant term corresponding to the

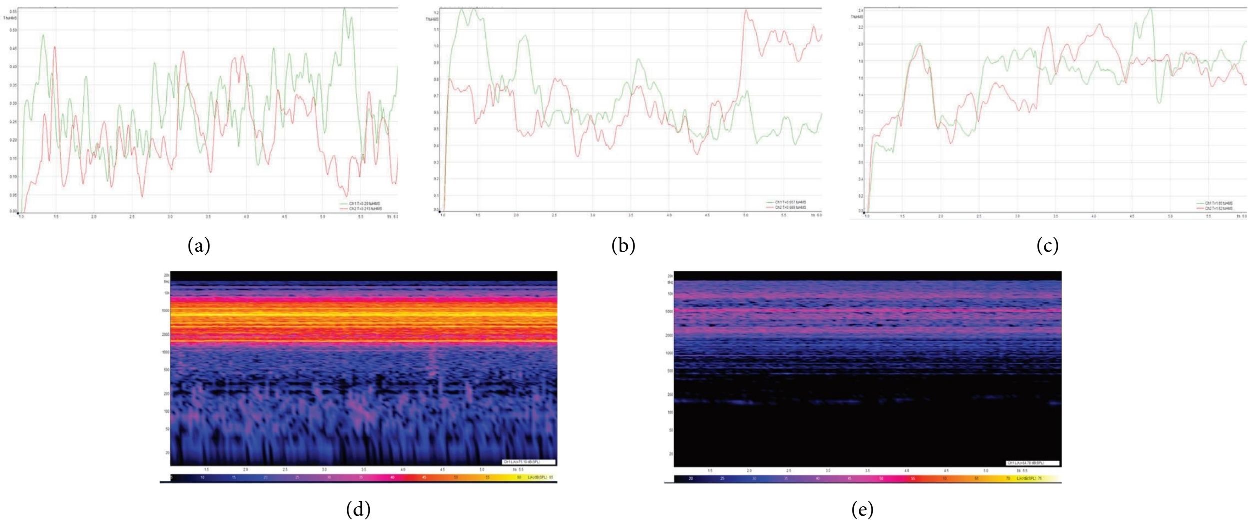


Figure 8: Tonality of (a) "low," (b) "medium," and (c) "high." (d)–(e) 2 different stimuli of spectrograms in the hanning window.

Table 1: Design elements.

Items	Categories						Characteristics
Head	 Flat single blade	 Flat multiple blades	 Round single blade	 Round two blades	 Round three blades	 Round five blades	(1) Flat multiple blades: 2 pieces or more than 2 pieces of blades
Neck	 Narrow neck	 Average neck	 Broad neck	 Neckless and seamless connection	 Neckless connection of two parts		(1) Narrow neck: $P_1 \geq 2$ (2) Average neck: $2 > P_1 > 1.5$ (3) Broad neck: $P_1 \leq 1.5$ (4) Neckless and seamless connection: there is no neck between the handle and head (5) Neckless connection of two parts: handle and head are closely connected as two parts

Table 1: Continued.

Items	Categories							Characteristics
Handle	 Narrow streamlined	 Average streamlined	 Broad streamlined	 Long cylindrical	 Short cylindrical	 Rounded rectangle	 Angular	(1) Narrow streamlined: streamlined model, $P_2 \leq 0.4$ (2) Average streamlined: streamlined model, $0.45 > P_2 > 0.4$ (3) Broad streamlined: streamlined model, $P_2 \geq 0.45$ (4) Long cylindrical: cylindrical model, $P_3 \leq 0.4$ (5) Short cylindrical: cylindrical model, $P_3 > 0.4$ (6) Round rectangle: the column with rounded rectangular sides (7) Angular: The combination of lines and angles
Switch (2 : 1)	 Round	 Rectangle	 Square-like	 Oval-like	 Triangle-like			(1) Square-like: rectangular model with rounded corners (2) Oval-like: oval-like model with the upper and lower edges of arc (3) Triangle-like: triangle-like model with three edges of arc
Switch activation (2 : 1)	 Slip-type	 Touch-tonality type						(1) Slip-type: slide to start (2) Touch-tonality type: press to start
Tonality	$0.1 \leq X > 0.6$ Low		$0.6 \leq X > 1.2$ Medium			$1.2 \leq X > 1.7$ High		(1) Tonality: classified by ArtmeiS 13.6 software measurement
Sound quality	$10 \leq X > 68$ Fluctuating and soft					$68 \leq X > 76$ Stable and powerful		(1) Stable and powerful/ fluctuating and soft: classified by ArtmeiS 13.6 software measurement

Table 2: QTTI prediction model results.

Items	Categories	Traditional/ fashion-forward			Soft/harder-edged			Cheap/premium			Sophisticated/ minimalistic		
		C	P	S	C	P	S	C	P	S	C	P	S
Head X_1	Flat single blade	−0.395	0.613	2	−0.613	0.801	1	−0.452	0.702	2	0.264	0.823	1
	Flat multiple blades	0.249			0.315			0.406			−0.219		
	Round single blade	−0.541			−0.230			−0.459			0.265		
	Round multiple blades	−0.089			−0.226			−0.367			0.255		
	Round three blades	0.236			0.272			0.308			−0.201		
	Round five blades	0.134			0.477			0.324			−0.337		

Table 2: Continued.

Items	Categories	Traditional/ fashion-forward			Soft/harder-edged			Cheap/premium			Sophisticated/ minimalistic		
		C	*P*	*S*	*C*	*P*	*S*	*C*	*P*	*S*	*C*	*P*	*S*
Neck X_2	Narrow neck	0.328			0.275			0.107			−0.286		
	Average neck	0.250			0.023			−0.051			0.043		
	Broad neck	−0.106	0.526	3	0.020	0.504	4	0.044	0.434	5	0.075	0.604	3
	Neckless and seamless connection	−0.212			−0.174			−0.156			0.085		
	Neckless connection of two parts	0.228			0.224			0.335			−0.016		
Handle X_3	Narrow streamlined	0.498			0.488			−0.504			−0.294		
	Average streamlined	0.119		1	0.007			−0.302			−0.153		
	Board streamlined	−0.192			−0.164			−0.291			0.102		
	Long cylindrical	−0.249	0.719		0.433	0.653	2	0.819	0.801	1	0.238	0.753	2
	Short cylindrical	−0.364			−0.233			0.874			0.260		
	Rounded rectangle	−0.350			−0.220			−0.207			0.137		
	Angular	0.657			0.018			0.976			−0.251		
Switch X_4	Round	−0.088			−0.046			−0.087			0.100		
	Rectangle	−0.206			−0.054			0.315			0.030		
	Square-like	−0.096	0.438	5	−0.005	0.203	6	−0.014	0.264	6	−0.124	0.428	5
	Oval-like	0.228			0.060			−0.020			−0.024		
	Triangle-like	0.299			0.100			0.052			0.016		
Switch activation X_5	Slip-type	0.092	0.145	7	0.057	0.125	7	0.104	0.157	7	−0.233	0.572	4
	Touch-tonality type	−0.028			−0.017			−0.032			0.0711		
Tonality X_6	High	−0.119			−0.168			−0.238			0.0241		
	Medium	−0.108	0.358	6	−0.007	0.393	5	−0.192	0.577	4	0.023	0.165	7
	Low	0.264			0.195			0.499			−0.055		
Sound quality X_7	Stable and powerful	0.276	0.489	4	0.272	0.612	3	0.357	0.588	3	0.072	0.295	6
	Fluctuating and soft	−0.215			−0.208			−0.273			−0.055		
Constant term (*C*)		3.876			3.401			3.633			4.224		
Complex correlation coefficient (*R*)		0.932			0.957			0.934			0.938		
Coefficient of determination (R^2)		0.868			0.917			0.872			0.879		

Notes: *C*, category score; *P*, partial correlation coefficient; *S*, sort.

different Kansei words, as shown in the following equation:

$$\begin{aligned} y_k = {} & a_{11}X_{11} + a_{12}X_{12} + a_{13}X_{13} + a_{14}X_{14} + a_{15}X_{15} + a_{16}X_{16} \\ & + a_{21}X_{21} + a_{22}X_{22} + a_{23}X_{23} + a_{24}X_{24} + a_{25}X_{25} \\ & + a_{31}X_{31} + a_{32}X_{32} + a_{33}X_{33} + a_{34}X_{34} + a_{35}X_{35} + a_{36}X_{36} + a_{37}X_{37} \\ & + a_{41}X_{41} + a_{42}X_{42} + a_{43}X_{43} + a_{44}X_{44} + a_{45}X_{45} \\ & + a_{51}X_{51} + a_{52}X_{52} \\ & + a_{61}X_{61} + a_{62}X_{62} + a_{63}X_{63} \\ & + a_{71}X_{71} + a_{72}X_{72} \\ & + \varepsilon_k. \end{aligned} \tag{1}$$

According to the QTTI multiple linear regression equation, 4 sets of “design elements-Kansei words” association prediction equations were constructed in this research as shown in the following equations:

「Y_1 Traditional/Fashion-forward」:

$$
\begin{aligned}
y_1 = {} & -0.395X_{11} + 0.249X_{12} - 0.541X_{13} - 0.089X_{14} + 0.236X_{15} + 0.134X_{16} \\
& + 0.328X_{21} + 0.250X_{22} - 0.106X_{23} - 0.212X_{24} + 0.228X_{25} \\
& + 0.498X_{31} + 0.119X_{32} - 0.192X_{33} - 0.249X_{34} - 0.364X_{35} - 0.350X_{36} + 0.657X_{37} \\
& - 0.088X_{41} - 0.206X_{42} + 0.096X_{43} + 0.228X_{44} + 0.299X_{45} \\
& - 0.092X_{51} - 0.028X_{52} \\
& - 0.119X_{61} - 0.108X_{62} + 0.264X_{63} \\
& + 0.276X_{71} - 0.208X_{72} \\
& + 3.876.
\end{aligned}
\tag{2}
$$

「Y2 Soft/Harder-edged」:

$$
\begin{aligned}
y_2 = {} & -0.613X_{11} + 0.315X_{12} - 0.230X_{13} - 0.226X_{14} + 0.272X_{15} + 0.477X_{16} \\
& + 0.275X_{21} + 0.023X_{22} + 0.020X_{23} - 0.174X_{24} + 0.224X_{25} \\
& + 0.488X_{31} + 0.007X_{32} - 0.164X_{33} + 0.433X_{34} - 0.233X_{35} - 0.220X_{36} + 0.018X_{37} \\
& - 0.046X_{41} - 0.054X_{42} - 0.005X_{43} + 0.060X_{44} + 0.100X_{45} \\
& + 0.057X_{51} - 0.017X_{52} \\
& - 0.168X_{61} - 0.007X_{62} + 0.195X_{63} \\
& + 0.272X_{71} - 0.208X_{72} \\
& + 3.401.
\end{aligned}
\tag{3}
$$

「Y3 Cheap/Premium」:

$$
\begin{aligned}
y_3 = {} & -0.452X_{11} + 0.406X_{12} - 0.459X_{13} - 0.367X_{14} + 0.308X_{15} + 0.324X_{16} \\
& + 0.107X_{21} - 0.051X_{22} - 0.044X_{23} - 0.156X_{24} + 0.335X_{25} \\
& - 0.504X_{31} - 0.302X_{32} - 0.291X_{33} + 0.819X_{34} + 0.873X_{35} - 0.207X_{36} + 0.976X_{37} \\
& - 0.087X_{41} + 0.315X_{42} - 0.014X_{43} - 0.020X_{44} - 0.052X_{45} \\
& + 0.104X_{51} - 0.032X_{52} \\
& - 0.238X_{61} - 0.192X_{62} + 0.499X_{63} \\
& + 0.357X_{71} - 0.273X_{72} \\
& + 3.633.
\end{aligned}
\tag{4}
$$

「Y4 Sophisticated/Minimalistic」:

$$\begin{aligned} y_4 = {} & 0.264X_{11} - 0.219X_{12} + 0.265X_{13} + 0.255X_{14} - 0.201X_{15} - 0.337X_{16} \\ & - 0.266X_{21} - 0.237X_{22} + 0.095X_{23} + 0.105X_{24} + 0.004X_{25} \\ & - 0.294X_{31} - 0.153X_{32} - 0.102X_{33} + 0.238X_{34} + 0.260X_{35} - 0.137X_{36} - 0.251X_{37} \\ & + 0.100X_{41} + 0.030X_{42} - 0.124X_{43} - 0.024X_{44} + 0.016X_{45} \\ & - 0.233X_{51} + 0.071X_{52} \\ & + 0.024X_{61} + 0.023X_{62} - 0.064X_{63} \\ & + 0.072X_{71} - 0.055X_{72} \\ & + 4.224. \end{aligned} \tag{5}$$

For the purpose of verifying the reliability of QTTI linear model, this research uses SPSS 23.0 to conduct dependent sample T-test on the Kansei evaluation values of 30 samples and the predicted values of QTTI regression equation. According to the test results, the P value is greater than 0.05 and there is no significant difference, so it shows that the QTTI linear model in this research is reliable.

4.3. The Establishment of Prediction Model Based on BPNN. In order to understand the difference between the prediction effect of QTTI linear model and BPNN nonlinear models, this research establishes the BPNN prediction model. It is confirmed that in the three-layer network, the input layer neural node is 30, the output neural node is 4, the hidden layer neural nodes are determined by equation (6) (see the following equation), where "r" is the number of hidden layer nodes, "l" is the number of input layer nodes, "k" is the number of output layer nodes, and "α" is a range constant from 1 to 10, by selecting the minimum mean squared error to determine the appropriate number of hidden layer nodes, as shown in Tables 3 and 4.

$$\mathrm{r} = \sqrt{\mathrm{l} + \mathrm{k}} + \alpha. \tag{6}$$

The transfer function combination of the input layer and the hidden layer is finally determined as "tansig" function and "purelin" function, and the heuristic algorithm is determined as algorithm [18], as shown in Figure 9(a). The determined 30 samples are used for training, 4 samples as validation samples, and the input layer data are normalized by equation (7).

$$\overline{h} = \frac{2\left(h_i - h_{\min}\right)}{h_{\min} - h_{\max}} - 1. \tag{7}$$

The network training times are set to 10,000 times, with an error of 0.0001. After training, the optimal number of nodes in the hidden layer is 8, and the best validation performance is $1.5396E-01$ at epoch 2, prediction model is set up, as shown in Figure 9(b).

4.4. The Establishment of Prediction Model Based on GA-BPNN. As the BPNN is aimed to provide the local optimal solution based on the gradient descent method, different initial weights may lead to problems, such as network convergence trapped in local extreme. To improve the prediction effect of BPNN, this research uses GA algorithm to optimize the parameters of weights and thresholds between BPNN neurons. The optimization process is shown in Figure 10.

The BPNN algorithm uses gradient descent method to seek local optimal solutions, thus different initial weights may cause the network to converge into local extreme points. In order to improve the prediction accuracy of BPNN, this research uses GA to optimize the parameters of weights and thresholds among BPNN neurons. In GA-BPNN, input variables, i.e., modeling + sound design elements (in binary format) will be involved in selection, crossover, and mutation operations as chromosomes.

I. Selection stage. After the algorithm randomly generates the first generation of chromosomes, the adaptation function is fitted with the 416 consumer Kansei evaluation values as the criterion, and the smaller the adaptation value, the superior the fit , and the function is established as shown in the following equation:

$$f(x) = \sum_{i=1}^{1} \dashv \left| C(i) - T(i) \right|, \tag{8}$$

where $C(i)$ is the consumer rating value i and $T(i)$ is the output rating value i.

In the first generation of chromosomes, individuals with a higher fitness level have a correspondingly higher probability of being selected, thereby selecting for the continuation of superior genes to form the next generation population. The selection method was determined to be an efficient and convenient roulette wheel selection method (Monte Carlo method), which divides the area of the roulette wheel by the retention probability of an individual, and calculates the probability of an individual being selected in proportion to its fitness function value, and performs genetic selection iterations to ensure that the overall fitness tends to be superior [36].

II. Crossover stage. For data in binary format, this research uses the multipoint crossover method [37] with a crossover probability of 0.7 to identify multiple breakpoints in the parent chromosome, and exchange genes between different chromosomes two-by-two in sequence to generate new chromosomes, this method can effectively break the solidified gene structure and significantly enhance the programme iteration (see Figure 11).

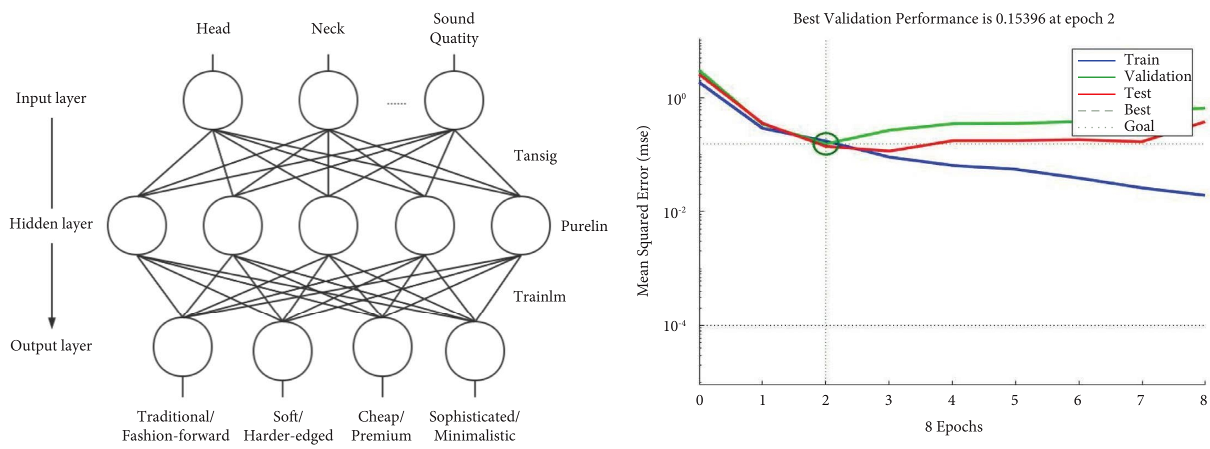


Figure 9: (a) BPNN training model. (b) Training and learning results of BPNN.

Table 3: Mean square error of the hidden layer neural nodes.

Hidden layer neural nodes	Mean squared error
6	$1.7001E-01$
7	$1.5637E-01$
8	$6.7788E-02$
9	$1.1394E-01$
10	$1.2375E-01$
11	$1.4698E-01$
12	$2.7746E-01$
13	$1.6952E-01$
14	$3.4262E-01$
15	$2.2486E-01$

Table 4: Relationship of BPNN layers.

Network layers	Neural nodes	Meaning
Input layer	30	30 design categories
Hidden layer	8	Processing data
Output layer	4	4 Kansei words

III. The mutation stage. The GA mimics the role of genetic variation in biological evolution by performing a random search locally at low frequencies in order to add fresh genes. This research uses a combination of Gaussian mutation and crossover operations with a variation probability of 0.2. The function is shown in the following equations:

$$\{v_k' = v_k + N(0, \sigma), \tag{9}$$

$$\left\{ f_c(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left((x-u)^2/2\sigma^2\right)} (-\infty < x < \infty), \right. \tag{10}$$

where $N(0, \sigma)$ denotes a rang of one-dimensional normally distributed random numbers with mean 0 and variance σ. The random numbers in this research obey a one-dimensional Gaussian distributed random number $N(u, \sigma)$ density function, u is the mean, σ is the standard deviation (variance step), and $N(0, 1)$ is the standard normal distribution.

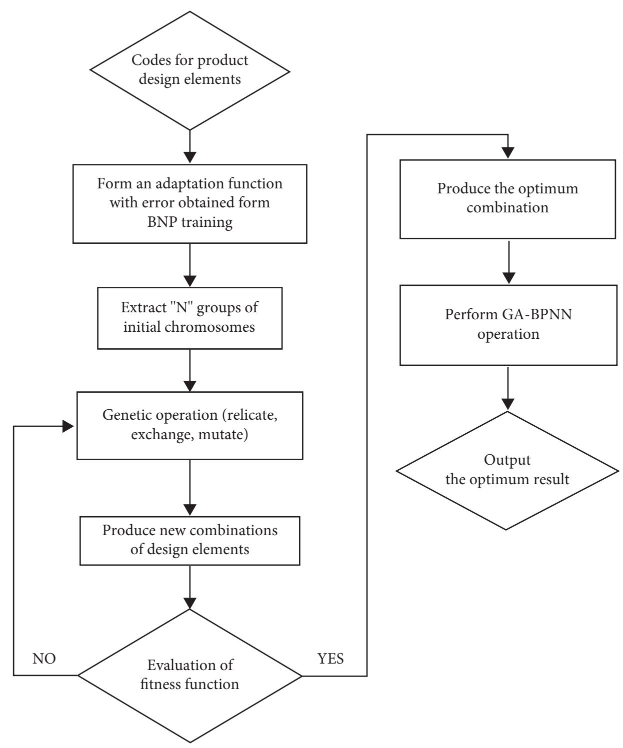


Figure 10: GA-BPNN optimization flow chart.

As a result, the corresponding control parameters of GA in this research are shown in Table 5. The model learning rate was set to 0.01 and the maximum number of iterations was set to 1000 [38]. The iterations were stopped and the model construction was completed when the best fitness is $7.8326E-02$, mean is $5.6009E-01$, iteration number is 11 times, and best validation performance is $1.9814E-01$ at epoch 5 (see Figure 12).

The design element codes of 4 groups of validation samples are taken as the input data of GA-BPNN. Figure 13 shows that the predicted values of GA-BPNN is closer to the Kansei evaluation values than the predicted values of BPNN, indicating that the prediction accuracy of GA-BPNN is higher than that of BPNN, as shown in Figure 13.

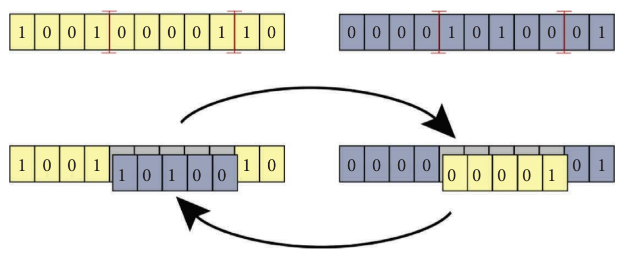
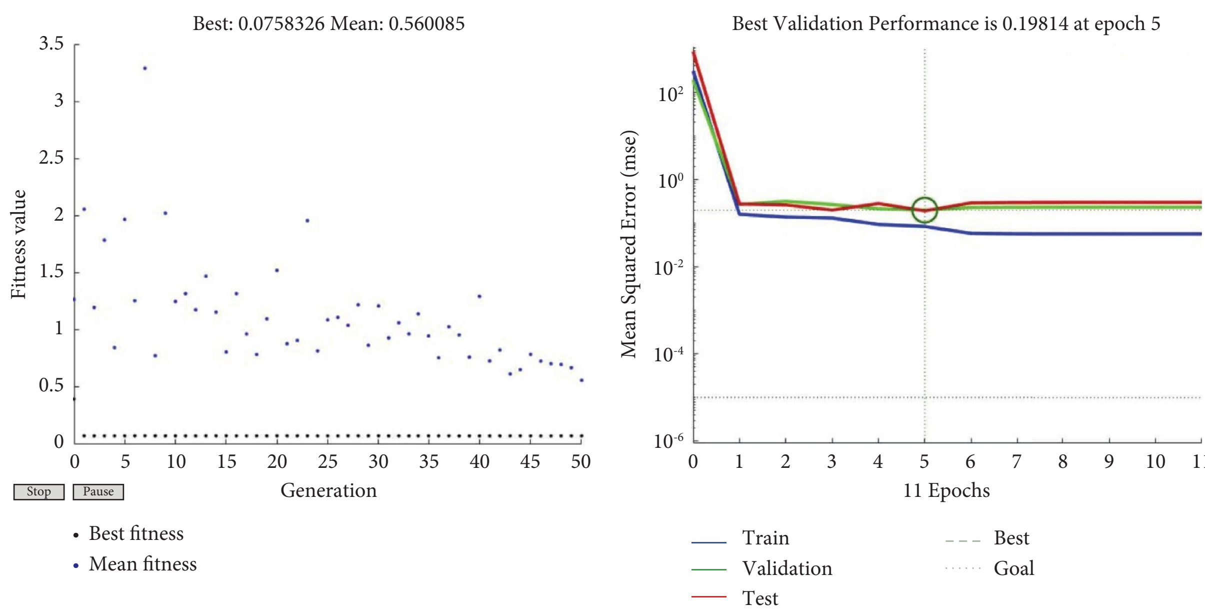


Figure 11: Crossover in GA.

Table 5: The control parameters of GA.

Population size (N)	Code length (l)	Crossover probabilities (p_c)	Probability of variation (p_m)	Maximum number of iterations (time)
30	30	0.7	0.2	1000



(a) (b)

Figure 12: (a) Genetic algorithm operation. (b) GA-BPNN model diagram.

Finally, the Kansei evaluation values of 30 samples and the predicted values of BPNN and GA-BPNN are tested by dependent sample T-test [39], and the P values are greater than 0.05, indicating that there is no significant difference and that the nonlinear models in this research are reliable.

4.5. Comparison of Linear and Nonlinear Prediction Models. 4 validation samples have been put into QTTI, BPNN, and GA-BPNN for predication. The prediction results are analyzed based on the Kansei evaluation values, and the error comparison method is used to compare the prediction accuracy of QTTI, BPNN, and GA-BPNN [40]. The calculation method of the relative error rate of each sample is as follows: ({| Kansei evaluation values - predicted values |/Kansei evaluation values} ∗ 100%), so as to determine the best prediction model, as shown in Table 6.

The results show that the average error rate of QTTI prediction under the four Kansei words is 11.67%, 6.57%, 9.82%, and 6.01%, respectively. The average error rate of BPNN is 26.35%, 18.35%, 24.97%, and 10.54%, respectively. The average error rate of GA-BPNN is 12.41%, 8.98%, 10.27%, and 7.18%, respectively. The comparison shows that QTTI has the best prediction effect and QTTI > GA-BPNN > BPNN in terms of the prediction effect.

4.6. The Analysis of the Influence of Various Design Elements on Kansei Words

4.6.1. Analysis on the Items Influences. Through the comparison of the above three models, it can be seen that QTTI model is the best. Therefore, the items and categories of electric shaver design elements are analyzed in this sequence: the partial correlation coefficient of the item indicates the

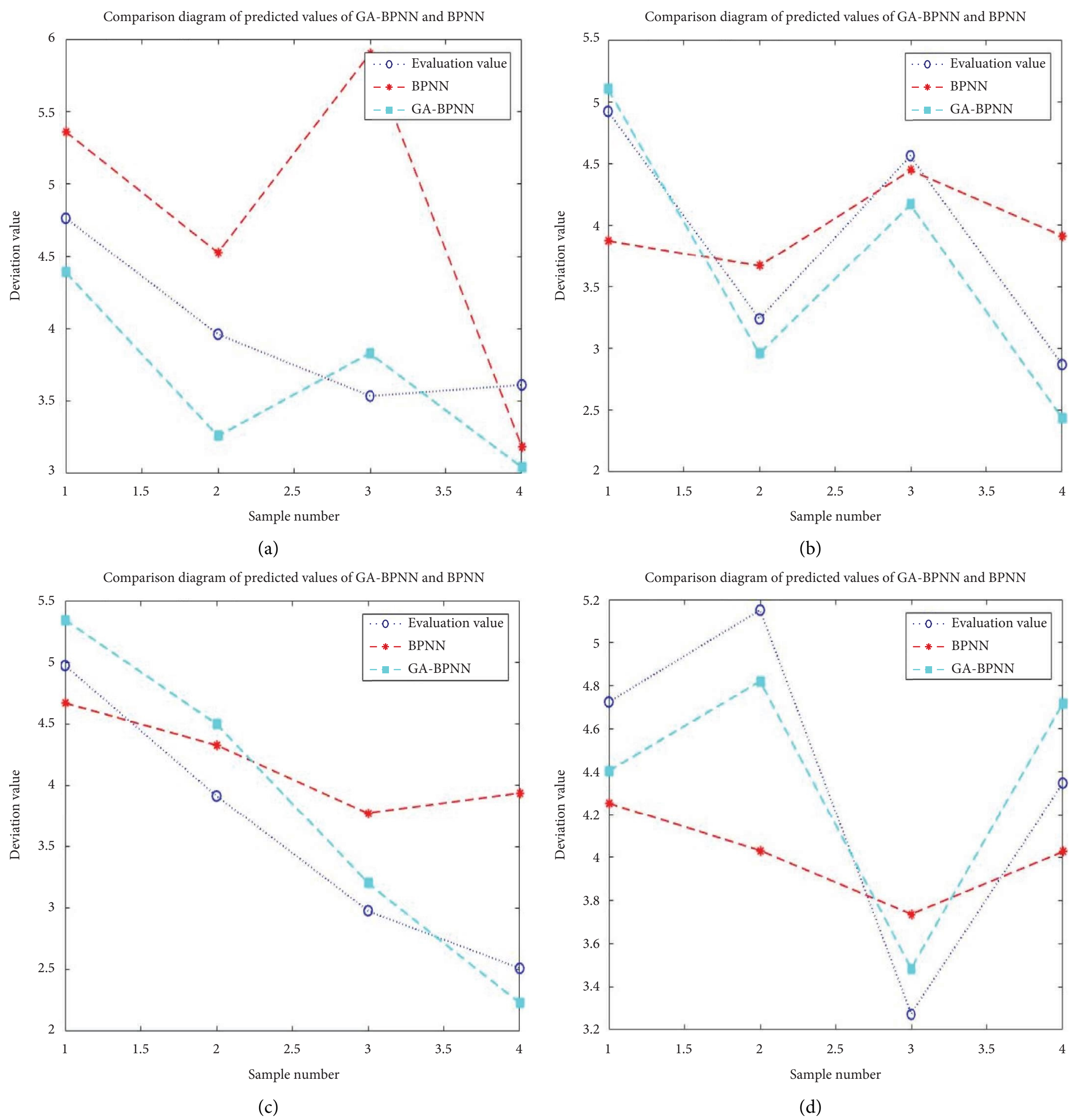


FIGURE 13: Kansei words of (a) “Traditional/fashion-forward,” (b) “Soft/harder-edged,” (c) “Cheap/premium,” and (d) “Sophisticated/minimalistic.”

correlation between various design element items and Kansei words. The larger the value, the stronger the degree of correlation with the imageries, that is, the higher the influence ability on the imageries.

In terms of “Traditional/Fashion-forward,” the most relevant item is the handle. The relevance is listed as follows: handle > head > neck > sound quality > switch > tonality > switch activation. In the design of “Traditional/Fashion-forward” electric shavers, priority should be given to the design elements with higher correlation coefficient. When there is a conflict between design items, it is suggested to use items that have greater impact on imagery. In terms of “Soft/Harder-edged,” the points obtained from each item is shown as follows: head > handle > sound quality > neck > tonality > switch > switch activation. In terms of “Cheap/Premium,” the points obtained from each item is shown as follows: handle > head > sound quality > neck > tonality > switch > switch activation. In terms of “Sophisticated/Minimalistic,” the points obtained from each item is shown as follows: head > handle > neck > switch activation > switch > sound quality > tonality.

4.6.2. Analysis on the Categories Influences. Category score indicates the correlation between category features and Kansei words of various modeling items. Specifically, a positive value indicates that category features and Kansei words are positively correlated, being more apt to the Kansei word on the right, while a negative value indicates the

Table 6: Comparison and analysis results of prediction models.

Sample	Adj		Traditional/fashion-forward	Soft/harder-edged	Cheap/premium	Sophisticated/minimalistic
Test 1	QTTI	AER	0.49	0.14	0.17	0.29
		RER	10.18%	2.90%	3.39%	6.15%
	BPNN	AER	0.60	1.05	0.30	0.47
		RER	12.51%	21.28%	6.12%	9.99%
	GA-BPNN	AER	0.38	0.18	0.37	0.32
		RER	7.88%	3.62%	7.45%	6.79%
Test 2	QTTI	AER	0.35	0.19	0.25	0.38
		RER	8.94%	5.89%	6.51%	8.42%
	BPNN	AER	0.56	0.43	0.41	0.46
		RER	14.24%	13.28%	10.53%	10.30%
	GA-BPNN	AER	0.70	0.28	0.58	0.33
		RER	17.70%	8.65%	14.91%	7.25%
Test 3	QTTI	AER	0.16	0.21	0.41	0.12
		RER	4.74%	4.52%	13.43%	3.73%
	BPNN	AER	2.37	0.12	0.79	0.46
		RER	66.92%	2.59%	26.65%	14.09%
	GA-BPNN	AER	0.30	0.40	0.23	0.21
		RER	8.38%	8.65%	7.57%	6.32%
Test 4	QTTI	AER	0.67	0.37	0.20	0.25
		RER	22.87%	12.96%	8.08%	5.75%
	BPNN	AER	0.43	1.04	1.42	0.32
		RER	11.76%	36.25%	56.59%	7.43%
	GA-BPNN	AER	0.57	0.43	0.28	0.37
		RER	15.71%	15.00%	11.17%	8.39%
AER (average)	QTTI:		11.67%	6.57%	9.82%	6.01%
	BPNN:		26.35%	18.35%	24.97%	10.54%
	GA-BPNN:		12.41%	8.98%	10.27%	7.18%

Notes: RER, relative error rate; AER, average error rate.

category and Kansei words are negatively correlated, tending towards the Kansei word on the left.

Under the Kansei word of "Traditional/Fashion-forward," the item with the highest partial correlation coefficient is the "handle." If the category gains a negative score, it belongs to the "Traditional" imageries. More negative values represent the more "Traditional" imageries and the ranking is as follows: short cylinder > rounded rectangle > broad streamlined > long cylinder. Among them, the category that gets a positive score is the "Fashion-forward" imagery. The ranking is angular > narrow streamlined > average streamlined. The importance of other Kansei words design categories can be analogized (as shown in Table 3).

5. Conclusion

In this research, firstly, the representative samples of electric shavers are selected by multidimensional scale and clustering analysis. Secondly, Kansei words of products is selected by expert group method. The product design elements are deconstructed by morphological analysis and are divided into 7 items and 30 corresponding categories. Finally, based on the combination of quantitative Kansei evaluation and product design elements, QTTI multivariate linear analysis, BPNN, and GA-BPNN non-linear analysis, the prediction models between product design elements and Kansei imageries are built, and the average error rate comparison method is used to compare these three analysis methods to choose the best prediction model. The results of this research are as follows:

(1) The product design elements are expanded to the two levels of visual modeling and auditory audio information, and multisensory design research is conducted in combination with multivariate linear analysis and nonlinear analysis, so as to more accurately understand Kansei imageries given to users by the overall design elements.

(2) QTTI, BPNN, and GA-BPNN methods are applied to establish the prediction models of product multisensory design. This research shows that they are all reliable, and GA significantly improved the prediction accuracy of BPNN, with QTTI having the best accuracy and GA-BPNN the second best.

(3) The influence of each design element item and category on the Kansei imagery: the rankings in the items of ① "Traditional/Fashion-forward," ② "Soft/Harder-edged," ③ "Cheap/Premium," and ④ "Sophisticated/Minimalistic" are as follows: ① handle > head > neck > sound quality > switch > tonality > switch activation; ② head > handle > sound quality > neck > tonality > switch > switch activation; ③ handle > head > sound quality > neck > tonality > switch > switch activation; and ④ head > handle > neck > switch activation > switch > sound quality > tonality. Taking

the "Traditional/Fashion-forward" as an example. The rankings categories in the "Traditional" imageries are as follows: short cylinder > rounded rectangle > broad streamlined > long cylinder. The rankings for the "Avant-garde" imagery are as follows: angular > narrow streamlined > average streamlined.

In conclusion, the systematic analysis approach adopted in this research can provide clear design indicators and references in the multisensory design and application of products, and improve the objectivity and logic of designs that are originally executed based on subjective experience. The research will be followed up by deep learning neural network to design and validate examples, with a view to applying the results to guide product innovation and design; and as this research method is only applicable to the research of product modeling and sound, but not colour, consideration may be given to introducing suitable research methods to explore the impact of colour on products in the future.

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

All authors contributed to the design and implementation of the research, to the analysis of the results, and to the writing of the manuscript.

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