Research on the Sensory Feeling of Product Design for Electric Toothbrush Based on Kansei Engineering and Back Propagation Neural Network

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Abstract

Over the years, China's electric toothbrush market has been expanding. Consumers pay more attention to the sensory feeling of product shape, under the premise of product function satisfaction. Therefore, this research collected 215,827 product reviews made by consumers online and 200 samples of varying electric toothbrush samples using a web crawler. Then, 3 groups of representative perceptual words were obtained from the extraction of numerous reviews via Word2vec, factor analysis and hierarchical cluster analysis. Meanwhile, with the help of morphological analysis, design elements of sample shape were de-structured on the 32 representative samples that were extracted from the collected sample using multi-dimensional scaling and hierarchical cluster analysis. On this basis, consumers' perceptual images were measured using semantic differential scale with 415 valid samples acquired in total. Finally, two relationship models between product design elements and consumers' perceptual images were established by quantitative theory type I (QTTI) and back propagation neural network. By comparison, the QTTI model has more accurate prediction. This study provides defined design indexes and references for designers' black box design patterns through establishing an effective model via combining web crawler technology and systematic analysis.

Keywords: Electric toothbrush, Kansei engineering, Web crawler, Word2Vec, Back Propagation Neural Network

1 Introduction

The market for electric toothbrush in China reached 21 billion yuan in 2021. Product functions become saturated with the continuously improving technology in today's consumer market. Instead, product morphology is designed in novelty along with product innovation. Under such a background, consumers are more aware of the emotional image conveyed by product modeling [1-2]. In essence, product is designed in accordance with user-centered principle. Hence, product design attributes should be considered according to user's internal psychology and emotional needs, making it more emotionally attractive [3-4]. The theory of Kansei engineering proposed by Japanese scholars, is mainly applied in the study of modeling innovation design for product perceptual image [5]. Kansei engineering is intended to develop products and services by way of transforming customers' psychological feelings and needs into design parameters. More specifically, consumers' mind perceptions are transformed into quantitative indicators by using the semantic differential scale (SDS). On this basis, a relationship model between product design features and user's perceptual image is built using regression analysis [6-9].

The quantified perceptual evaluation can facilitate designers to design products in conformity with consumers' emotional needs on the premise of obtaining objective data of consumer's perceptual cognition of products and fully understanding consumers' preferences and perceptions [10]. Therefore, it is of great significance to reasonably extract consumers' mind perceptions. Manual means such as questionnaires, KJ (Kawakita Jiro, KJ) method, and literature materials were adopted for collecting perceptual vocabulary and product samples in most of the previous studies [11-12]. Although these means could provide materials and data required by the study, they have limitations in small data scale and low efficiency in data collection and processing. Moreover, these traditional data acquisition means cannot accurately reflect emotional factors of users for their acquisitions are mostly performed based on expert thinking [13-15]. Online shopping has become a dominant means of consumption with the development of computer technology and the Internet. In this case, people also share a variety of reviews online while buying goods. Based on data, an information network connecting product attributes and user feelings can be constituted [16], with accurate perceptual information of consumers. Hence, one of the highlights in this study is to extract users' valuable perceptual vocabulary from online reviews of products collected by python Web crawlers with the help of techniques such as text mining and natural language processing (NLP).

The degree of correlation between morphological design elements of product and perceptual image is normally presented by the quantitative theory type I (QTTI) based on multiple linear regression in traditional Kansei engineering. But a nonlinear model is built in this paper upon the introduction of back-propagation neural network (BPNN) to

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compare it with the linear model of QTTI with a consideration in people's non-linear feeling feature [17]. Based on the comparison result, the superior relationship model will be applied in the optimized design of product modeling.

2 Literature Review

2.1 Research Status of Electric Toothbrush

Electric toothbrush, a novel force in the cleaning appliance market, has been profoundly discussed in many studies. For instance, Driesen proposed that a pulsating electric toothbrush provides a better cleaning efficacy than an oscillating/ rotating electric toothbrush through simulating plaque residues in various oral parts with a computer vision system [18]. Chen put forward a recurrent probabilistic neural network for toothbrush gesture recognition, contributing to a great reduction in the computing power of hardware device, in an attempt to cope with the problem of high computing resources required for the real-time signal processing of nine-axis inertial sensing and toothbrush gesture recognition of electric toothbrush [19]. It can be observed that technological improvement of electric toothbrush has been principally concerned in previous studies. Since emotional image conveyed by product modeling becomes essential in the product competitiveness when the function tends to be saturated [20-21], this study was conducted for investigating sensory feelings of electric toothbrush modeling design through a systematic and quantitative analysis.

2.2 Web Crawler and NLP

Web crawler and NLP technology are adopted for data acquisition thanks to the continuous development of network technology and deep learning [22-23]. Lai acquired reviews concerning new energy vehicles via Scrapy crawler and investigated the hidden relationship between reviews in accordance with a deep learning NLP model [24]. Jiao obtained consumers' perceptual vocabularies that are highly related to products through screening a large amount of text data of product online reviews automatically extracted by NLP [25]. This paper mined product reviews and samples in accordance with the working principle of web crawlers automatically traversing the network for downloading documents via links between web pages [26]. As word2vec is a word prediction model based on the core algorithm of neural network, it can predict and output the relevant perceptual vocabularies from the input keyword through skip-gram algorithm according to the review context [27], so it can automatically identify and extract modeling perceptual vocabularies through natural language processing technology.

2.3 Quantification Theory TypeI

QTTI is one of the popular methods adopted to establish a linear relationship for regression analysis in Kansei engineering, which can predict a single dependent variable from multiple independent variables using a linear equation. In this way, a quantitative and qualitative analysis can be completed. Mitsuo developed cosmetic containers through multiple regression analysis with QTTI based on Kansei engineering [28]. Wei applied QTTI to optimize the perfume bottle design for the best combination of product morphological elements [29]. Therefore, the product morphology can be first decomposed into various items and categories, and used as independent variables. Then, taking the perception evaluation as the dependent variable, QTT Ⅰ is used to establish the linear relationship model to optimize the product modeling.

2.4 Back-Propagation Neural Network

Artificial Neural network is most typical in nonlinear regression analysis, of which BPNN has been extensively applied in the field of product optimization design for it can learn and store numerous input-output mapping relationships [30]. Tung established the relationship between static icons and user's perception to acquire a user-centered icon design scheme for mobile device interface through combining design features of icon with user's emotional cognition upon the proposal of a BPNN-based icon design method, providing a design thought that is consistent with user requirements for interface/ icon design [31]. More precisely, a mapping relationship model between design features of electric toothbrushes and product perceptual images was established upon the introduction of BPNN. In this way, the predictive effects of linear and nonlinear models can be compared.

3 Method and Procedure

A relationship model between the design elements of electric toothbrushes and user's perceptual images was also set up. The research process is composed of four parts, as shown in Figure 1.

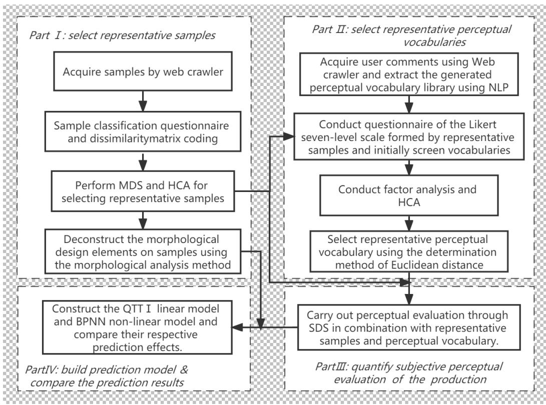

Figure 1. Research flow chart

3.1 Data Acquisition

The application of big data analysis methods in consumer reviews is useful and practical [32]. The basic process of Python web crawler acquiring web page data is presented below (see Figure 2). i. Initiation of a request: A request that might contain additional header information is initiated to the server through a URL (step 1-3). ii. Acquisition of response content: The normally-responded server receives a response, or the requested web page content that might contain HTML, JSON (JavaScript Object Notation, is a lightweight data-interchange format.) strings or binary data (such as video, pictures, text), etc. (step 4-6). iii. Content parsing: The HTML code can be parsed using web parser, and JSON data can be parsed and processed upon being converted into a JSON object (step 7-8). iv. Data saving: data collected are saved in a local file or a database (step 9). Therefore, this paper can save the parsed data of the response content into text to a local file upon initiating a request to an e-commerce website server.

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To be specific, 20 brands such as Philips, Oral B, MIUI, and Huawei, etc. were searched on Jingdong Mall with “electric toothbrush” as the keyword. By sorting the reviews of each brand in a descending order, the top 10 products were crawled respectively for each brand with the minimum review page for each sample setting as 100 pages in the python-programmed crawler. Finally, review and sample database were set up with 215,827 valid reviews and 200 samples.

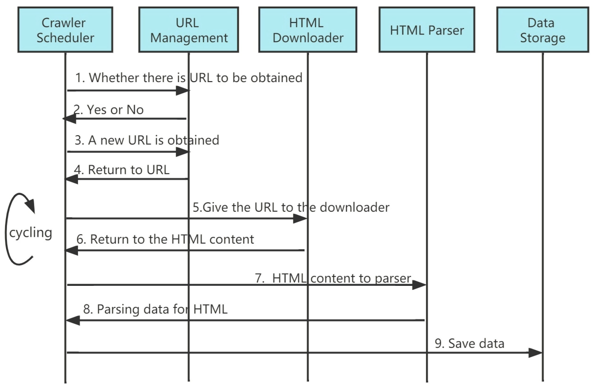


Figure 2. WebCrawler frame

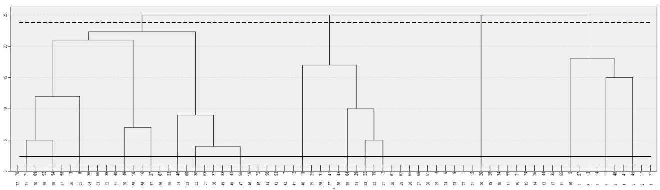
3.2 Representative Samples

72 samples were obtained after the preliminary screen of the sample database as per similarity. And representative samples were finally determined through screened those samples objectively using the sample cluster questionnaires, multi-dimensional scaling (MDS) method and hierarchical cluster analysis.

Specifically, similar samples were grouped by 25 graduate students and undergraduate students majoring in design, and related product designers upon browsing all samples according to subjective feelings. Results of the sample classification were then coded, forming a 72*72 dissimilarity matrix.

The coordinate positions from 2 to 6 dimensions and the STREE value as well as RSQ value in different dimensions were obtained after the MDS was adopted to reduce the dimension of dissimilarity matrix data in SPSS 23.0 software. To be concrete, the STREE value is for measuring the fitting effect, the smaller the value, the better the fitting effect will be [33], while the RSQ value determined by the corresponding distance, is the ratio of the variance of data observed in the partition, the greater the value, the better the effect will be. A six-dimensional vector space is preferred in this analysis. A cluster hierarchy was obtained through conducting cluster analysis with the Ward method after 72 samples were converted into six-dimensional coordinate values, as shown in Figure 3.

16 categories were selected for the number of clustering for considering the accuracy of the predictive model established in the later study and the load of respondents who receive questionnaires, since morphological element deconstruction analysis [34], SDS, QTTI linear regression analysis, and BPNN nonlinear analysis should be adopted on electric toothbrush samples in the subsequent experiment. Meanwhile, each sample in each group (more than 2 samples) was voted by 5 graduate students majoring in design in sequence. After that, the 2 samples with the greatest number of votes in each clustering group were used as representative samples. In total, there are 32 representative samples, as shown in Figure 4. Based on this, one sample is selected from each of the 4 groups in Figure 3 (see dotted lines), that is, a total of 4 samples were selected as test samples for subsequent comparison of model prediction [35]. And the remaining samples were adopted for model building and training.



Note： ···· To extract the 4 groups in the test set.
— To extract the 32 representative samples.

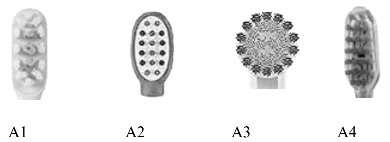
Figure 3. Clustering hierarchical diagram

Figure 4. Representative samples

3.3 Destruction and Coding of Morphological Elements

The product morphology was deconstructed by morphological analysis in this experiment. By referring to 32 electric toothbrush samples, 6 items and 25 categories concerning product morphology design elements were obtained by deconstruction analysis, as shown in Table 1. Meanwhile, coding design was performed on these samples according to their respective items and categories.

Table 1. Items and categories of design elements

Item	Category					
Toothbrush head (scale, 2:1)						
	A1 Rounded rectangle	A2 Oval	A3 Round	A4 Trapezoid		
Toothbrush neck (1.5:1)						
	B1 Rectilinear	B2 Arc	B3 Trapezoid			
Toothbrus handle (1:1)						
	C1 Cylinder	C2 Cube	C3 Bionic	C4 Frustum cone	C5 circular truncated cone	C6 Arc
Toothbrush handle Decoration (1.5:1)						
	D1 Line stripe pattern	D2 Ridged pattern	D3 Cartoon pattern	D4 Dotted pattern	D5 Smooth & patternless	
Toothbrush neck and Handle Connection (1.5:1)						
	E1 Continuous	E2 Rounded connection	E3 Class connection			
Switch (2:1)						
	F1 Rectangle	F2 Round	F3 Oval	F4 Rhombus		

3.4 Representative Perceptual Vocabulary

Three representative perceptual vocabulary was determined through first extracting perceptual vocabulary of modeling from the online reviews using Word2Vec neural network [36] and then screening the extracted perceptual vocabulary objectively through factor analysis and hierarchical cluster analysis [37].

3.4.1 Construction of A Database of Perceptual Vocabulary

A semantic network was generated from the co-occurrence word frequency matrix obtained through the statistics of high-frequency vocabulary after performing word segmentation and data cleaning on the comment text, which was then analyzed to obtained the distribution of user review (incl. appearance, effect, and function, etc.). Moreover, the "modeling" keyword was considered as the input word with the help of Word2Vec model for extracting the perceptual vocabulary of modeling dimension. Also, the output relevant perceptual vocabularies are set as adjective using the skip-gram algorithm. Ultimately, a database of perceptual vocabulary was built with 140 vocabulary extracted.

3.4.2 Factor Analysis

At first, 15 perceptual vocabulary was filtered through two rounds of screening by the focus group in order to reduce the experimental subjects' loads caused by numerous vocabularies in the SDS evaluation with a consideration in overlapping or negative meanings of vocabulary. Next, 45 experimental subjects were invited for evaluating the 7-point Likert scale questionnaire formed by 32 samples. Questionnaire data were utilized for the KMO sampling suitability test during factor analysis. The closer the KMO value to 1, the stronger the correlation between variables, and the more suitable the original variables for factor analysis. Upon calculation, the KMO value was obtained as 0.764, and the significance as 0.000. Based on this, factor analysis and statistics were performed through the maximum variance rotation using the principal component analysis method, with the eigenvalues extracted more than 1, and rotation axis performed using the maximum variance method. Three factors can be extracted according to the observation of the scree plot, with a rotation component matrix obtained.

3.4.3 Hierarchical Cluster Analysis

The rotation component matrix is clustered using the Ward method. And the classification is divided into 3 groups according to the clustering hierarchy (see Figure 5). Meanwhile, Euclidean distances between various vocabulary and its center were calculated. On this basis, the sample with the shortest distance was regarded as the final representative word.

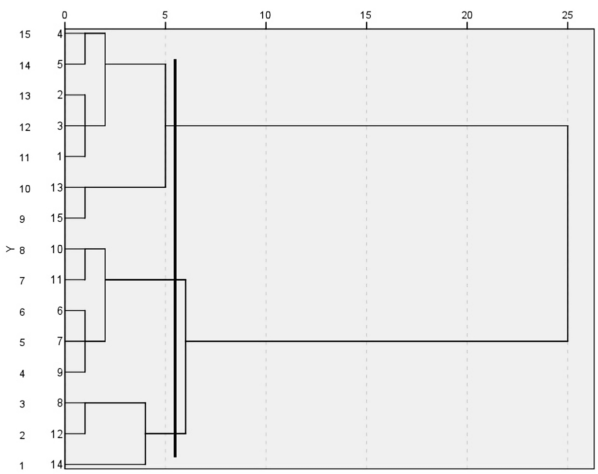


Figure 5. Clustering hierarchical diagram

Representative vocabulary is obtained from the one with the shortest Euclidean distance, as shown in Table 2 and paired with respective antonyms. Through which, "Youthful/Mature", "High-end/Low-end", and "Minimalistic/Sophisticated" were deemed as three groups of representative perceptual vocabulary.

Table 2. Euclidean distances

Group	Words	Factor 1	Factor 2	Factor 3	**ED**	DS
1	Trendy	0.903	0.219	-0.133	0.523	0.273
	Gorgeous	0.886	-0.019	0.029	0.376	0.142
	Exquisite	0.884	0.153	0.158	0.250	0.062
	Youthful	**0.763**	**-0.059**	**0.461**	**0.205**	**0.042**
	Artful	0.760	-0.169	0.433	0.291	0.085
	Fantastic	0.491	0.114	0.785	0.498	0.248
	Adorable	0.388	0.504	0.683	0.621	0.386
Center coordinates of cluster		0.725	0.106	0.345		
2	Straight	-0.389	0.864	-0.124	0.386	0.149
	Minimalistic	**-0.617**	**0.658**	**-0.367**	**0.364**	**0.133**
	Harder-edged	0.237	0.434	-0.764	0.641	0.410
Center coordinates of cluster		-0.256	0.652	-0.418		
3	Individualized	-0.003	0.895	-0.050	0.258	0.067
	Gracious	-0.038	0.895	-0.217	0.375	0.140
	High-end	**0.135**	**0.780**	**0.181**	**0.172**	**0.030**
	Luxurious	0.504	0.733	0.070	0.292	0.085
	Stable	0.519	0.727	0.196	0.345	0.119
Center coordinates of cluster		0.223	0.806	0.036		

ED: Euclidean Distance, DS: Distance Square

3.5 Perceptual Evaluation

32 electric toothbrush samples and 3 pairs of perceptual vocabulary were used to form the SDS of this study. Then, experimental subjects were required to evaluate the samples on a 7-point SDS that can express the psychological perception of consumers of varying degrees. At last, 456 questionnaires were recovered, with 41 invalid questionnaires excluded. And the code of sample modeling elements and the evaluation value of questionnaire were applied to QTTI multiple regression analysis and BPNN nonlinear regression analysis for model establishment.

4 Results and Discussion

4.1 Analysis of the Relationship between Modeling Elements and Perceptual Images based on QTTI

4.1.1 Establishment of the QTTI Multiple Linear Regression Equation

QTTI establishes a linear relationship between quantitative and qualitative variables in the form of a multiple linear regression equation (Eq. 1). In this paper, QTTI analysis was performed with categories of electric toothbrush modeling as independent variables, and the perceptual image evaluation value of each sample as dependent variables.

$$\begin{aligned} y_k = {} & a_{11}X_{11} + a_{12}X_{12} + a_{13}X_{13} + a_{14}X_{14} \\ & + a_{21}X_{21} + a_{22}X_{22} + a_{23}X_{23} \\ & + a_{31}X_{31} + a_{32}X_{32} + a_{33}X_{33} + a_{34}X_{34} + a_{35}X_{35} + a_{36}X_{36} \\ & + a_{41}X_{41} + a_{42}X_{42} + a_{43}X_{43} + a_{44}X_{44} + a_{45}X_{45} \\ & + a_{51}X_{51} + a_{52}X_{52} + a_{53}X_{53} \\ & + a_{61}X_{61} + a_{62}X_{62} + a_{63}X_{63} + a_{64}X_{64} \\ & + \varepsilon_k \end{aligned} \quad (1)$$

Table 3. QTTI analysis results

Design item	Category	Y1 Mature/Youthful Category point	Y1 Partial correlation coefficient	Y1 Influence ranking	Y2 Low-end/High-end Category point	Y2 Partial correlation coefficient	Y2 Influence ranking	Y3 Sophisticated/Minimalistic Category point	Y3 Partial correlation	Y3 Influence ranking
Toothbrush head X1	Rounded rectangle X_{11}	-0.168	0.689	3	0.030	0.588	3	-0.073	0.519	4
	Oval X_{12}	0.170			0.052			0.064		
	Round X_{13}	0.092			-0.115			0.166		
	Trapezoid X_{14}	-0.213			-0.190			-0.177		
Toothbrush neck X_2	Straight X_{21}	-0.123	0.544	4	-0.170	0.488	4	0.110	0.231	6
	Arc X_{22}	0.083			0.017			-0.001		
	Trapezoid X_{23}	-0.162			0.028			-0.018		
Toothbrush handle X_3	Cylinder X_{31}	-0.123	0.732	2	0.088	0.816	1	0.104	0.705	2
	Square X_{32}	-0.194			-0.242			-0.216		
	Bionic X_{33}	0.370			-0.343			-0.392		
	Frustum Cone X_{34}	0.162			0.135			0.092		
	Circular truncated Cone X_{35}	0.154			0.100			0.070		
	Arc X_{36}	0.206			-0.163			-0.163		
Toothbrush handle decoration X_4	Line stripe decoration X_{41}	-0.293	0.849	1	0.123	0.648	2	-0.214	0.852	1
	Ridged decoration X_{42}	0.189			0.147			-0.288		
	Cartoon decoration X_{43}	0.339			-0.107			-0.354		
	Dotted Decoration X_{44}	-0.476			-0.092			-0.196		
	Smooth and patternless X_{45}	0.123			-0.045			0.292		
Toothbrush neck and handle Connection X_5	Continuous X_{51}	0.016	0.170	6	-0.035	0.315	5	0.143	0.676	3
	Rounded connection X_{52}	0.011			0.025			-0.120		
	Corner connection X_{53}	-0.063			0.054			-0.186		
Switch X_6	Rounded rectangle X_{61}	-0.070	0.281	5	-0.011	0.155	6	-0.111	0.344	5
	Round X_{62}	-0.021			-0.014			0.034		
	Oval X_{63}	0.033			0.025			0.018		
	Rhombus X64	0.132			0.021			-0.160		
Constant term		4.109			4.246			3.899		
Multiple correlation coefficient (R)		0.940			0.906			0.926		
Coefficient of determination (R^2)		0.883			0.821			0.857		

Where, if represents the scoring point of the jth category under the ith modeling item, it will be considered as the coefficient of the multiple linear regression equation; X_{11}, X_{12}, X_{13}......X_{63}, and X_{64} representing each category are independent variables; represents the constant term of the multiple linear regression equation under the kth group of perceptual vocabulary.

QTTI analysis was performed on modeling element codes and Kensei evaluation values of 28 experimental samples using SPSS software. Results are shown in Table 3. The coefficient of determination R^2 represents the overall fitting degree. 0.883, the coefficient of determination of "Mature/Youthful", for example, indicates that the regression equation can explain 88% of the variations in the dependent variable. And the other two groups of perceptual images were greater than 0.70, presenting a favorable degree of fitting.

4.1.2 Analysis of Influence of Various Modeling Items and Categories on Perceptual Image

Based on the comparison of various partial correlation coefficients, the ranking on influences of design elements on the consumer's emotional image are concluded as below:

(i) Items impact analysis

Influences of various items under the "Mature/Youthful" perceptual image are ranked as:

Toothbrush handle decoration> toothbrush handle> toothbrush head > toothbrush neck > switch > connection of toothbrush neck and handle, of which the partial correlation coefficient of the "toothbrush handle decoration" is 0.849, being most correlated with the "Mature/Youthful". The ranking indicates that "toothbrush handle decoration", "toothbrush handle", and "toothbrush head" are successively prioritized modeling elements concerned in the design of "Mature/Youthful" image for the electric toothbrush.

Influences of various items under the "Low-end/High-end" perceptual image are ranked as:

Toothbrush handle > toothbrush handle decoration > toothbrush head > toothbrush neck > connection of toothbrush neck and handle > Switch, of which the partial correlation coefficient of the "toothbrush handle" is 0.816, being most correlated with the "Low-end/High-end". The ranking indicates that "toothbrush handle", "toothbrush handle decoration", and "toothbrush head" are successively prioritized modeling elements concerned in the design of "Low-end/High-end" image for the electric toothbrush.

Influences of various items under the "Sophisticated/Minimalistic" perceptual image are ranked as:

Toothbrush handle decoration > toothbrush handle > connection of toothbrush neck and handle > toothbrush head > switch > toothbrush neck, of which the partial correlation coefficient of the "toothbrush handle decoration" is 0.852, being most correlated with the "Sophisticated/Minimalistic" image. The ranking indicates that "toothbrush handle decoration", "toothbrush handle", "connection of toothbrush neck and handle", and "toothbrush head" are successively prioritized modeling elements of the electric toothbrush in the design of "Sophisticated/Minimalistic" perceptual image.

(ii) Categories impact analysis

A more particular understanding of the degree of the influence of category on the perceptual image can be obtained from scoring points. For example, when the category scoring point of "Mature/Youthful" is positive, it indicates the category is biased towards the "Youthful" image on the right; when the category scoring point is negative, it means that the category is biased towards the "Mature" image on the left. Moreover, the greater the absolute value indicates the higher the degree of being biased towards the image. For example, the category scoring point of the "Youthful" image is ranked as cartoon decoration > ridged decoration > smooth and patternless surface, while the scoring point of the "Mature" image is ranked as dotted decoration >line stripe decoration in the modeling design of "toothbrush handle decoration" item in "Mature/Youthful". Cartoon decoration, smooth surface, and ridged decoration are positive values, presenting the "Youthful" image, with the cartoon decoration exerting the greatest influence. On the contrary, the dotted decoration and line stripe decoration are negative values, presenting the "Mature" image, with the dotted decoration exerting the greatest influence. The rest can be analogized in the same manner (Table 3).

4.1.3 Construction of QTTI Model

The multiple linear regression equation of QTTI (as shown in 4-1) was formed with 25 categories of electric toothbrush modeling elements as independent variables, consumer's perceptual image evaluation as dependent variables, and scoring points of all items as coefficients. Based on this, three groups of multiple linear regression equations between the characteristics of modeling elements and perceptual image evaluation in this study can be constructed as:

Y_1 "Mature/Youthful":

$$\begin{aligned} y_1 = & -0.168\,X_{11} + 0.170\,X_{12} + 0.092\,X_{13} - 0.213\,X_{14} \\ & -0.123\,X_{21} + 0.083\,X_{22} - 0.162\,X_{23} \\ & -0.123\,X_{31} - 0.194\,X_{32} + 0.370\,X_{33} + 0.162\,X_{34} + 0.154\,X_{35} + 0.206\,X_{36} \\ & -0.293\,X_{41} + 0.189\,X_{42} + 0.339\,X_{43} - 0.476\,X_{44} + 0.123\,X_{45} \\ & +0.016\,X_{51} + 0.011\,X_{52} - 0.063\,X_{53} \\ & -0.070\,X_{61} - 0.021\,X_{62} + 0.033\,X_{63} + 0.132\,X_{64} \\ & +4.109 \end{aligned} \tag{2}$$

Y_2 "Low-end/High-end":

$$\begin{aligned} y_2 = & \; 0.030\,X_{11} + 0.052\,X_{12} - 0.115\,X_{13} - 0.190\,X_{14} \\ & -0.170\,X_{21} + 0.017\,X_{22} + 0.028\,X_{23} \\ & +0.088\,X_{31} - 0.242\,X_{32} - 0.343\,X_{33} + 0.135\,X_{34} + 0.100\,X_{35} - 0.163\,X_{36} \\ & +0.123\,X_{41} + 0.147\,X_{42} - 0.107\,X_{43} - 0.092\,X_{44} - 0.045\,X_{45} \\ & -0.035\,X_{51} + 0.025\,X_{52} + 0.054\,X_{53} \\ & -0.011\,X_{61} - 0.014\,X_{62} + 0.025\,X_{63} + 0.021\,X_{64} \\ & +4.246 \end{aligned} \tag{3}$$

Y_3 "Sophisticated/Minimalistic":

$$\begin{aligned} y_3 = & -0.073\,X_{11} + 0.064\,X_{12} + 0.167\,X_{13} - 0.177\,X_{14} \\ & +0.110\,X_{21} - 0.011\,X_{22} - 0.018\,X_{23} \\ & +0.104\,X_{31} - 0.216\,X_{32} - 0.380\,X_{33} + 0.092\,X_{34} + 0.070\,X_{35} - 0.163\,X_{36} \\ & -0.214\,X_{41} - 0.288\,X_{42} - 0.354\,X_{43} - 0.196\,X_{44} + 0.292\,X_{45} \\ & +0.143\,X_{51} - 0.120\,X_{52} - 0.186\,X_{53} \\ & -0.111\,X_{61} + 0.034\,X_{62} + 0.018\,X_{63} - 0.160\,X_{64} \\ & +3.899 \end{aligned} \tag{4}$$

4.1.4 Verification of QTTI Model

To verify the reliability of the QTTI linear prediction model, perceptual evaluation values and linearly predicted values of 28 experimental samples were tested through the verification of pared samples t-test using SPSS. Note that the predicted value was calculated by substituting the codes of various samples into the corresponding regression equations. According to test results of all 3 groups of perceptual vocabulary, the p-values being greater than 0.05 indicate no significant difference is found between the above two values. It is reliable to apply the QTTI linear prediction model in this study.

4.2 Analysis of the Relationship between Modeling Elements and Perceptual Images based on BPNN

28 design elements of experimental samples were encoded to form an input layer, while the perceptual evaluation values form an output layer (Table 4) for network training. The number of hidden layer nodes can be determined by Eq. 5 using Matlab in combination with the minimum error index by trial and error (note that r is the number of hidden layer node; l is the number of input layer node, and k is the number of output layer node). By taking the tan-sigmoid function as the transfer function of the first layer of the network, the input range can be mapped from (-∞, +∞) to the (-1, +1). Then, the purelin function is used for normalizing the perceptual evaluation value as the transfer function in the second layer [38]. Meanwhile, the trainlm algorithm is used for network training, with the training times are set to 1000, with the learning rate and the training target error set to 0.01 and 0.00001, respectively. Finally, the error accuracy reaches 2.30e-6, which is less than the preset 1e-05, as shown in Figure 6. At this point, model training is completed.

Table 4. Calibration of input and output layers

Network layer	Qty. of Nodes	Meaning
Input layer	25	25 design categories
Output layer	3	3 groups of perceptual vocabulary

$$r = \sqrt{l+k} + \alpha \qquad (\alpha=1\sim10) \tag{5}$$

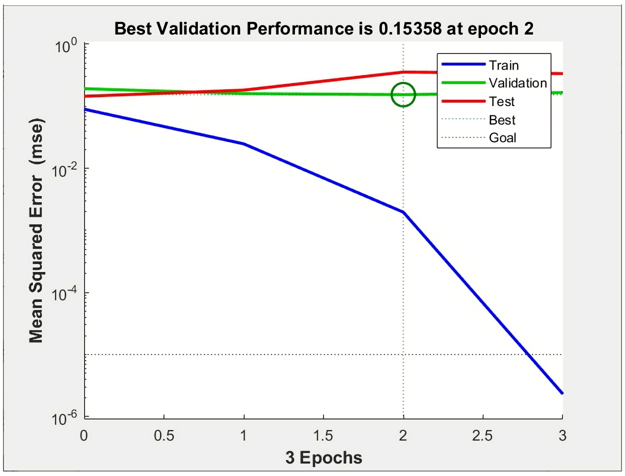


Figure 6. Simulation of BPNN training

To verify the reliability of the BPNN model, the predicted value was first obtained by simulating the experimental sample through the BPNN model. Then, the questionnaire evaluation value and the predicted value were used as the test objects for the pared samples t-test. The test results show that the p values are all greater than 0.05 (in BPNN model of 3 pairs of perceptual vocabularies), no significant difference between the predicted values and the evaluation values indicate that it is reliable to apply the BPNN model for the nonlinear prediction.

4.3 Predictive Comparison between the QTTI Model and BPNN Model

The average error rate comparison method was adopted as the evaluation standard for comparing the performance of the two models for predicting product perceptual image [39]. Absolute error value, relative error rate (absolute relative error value/ actual evaluation value) and the average error rate of the predicted value and the perceptual evaluation value were calculated for four test samples under the two models, as shown in Table 5.

Table 5. Errors of two models

Sample	adj		Mature/ Youthful	Low-end/ High-end	Sophisticated/ Minimalistic
Test 1	QT	AEV	0.9608	0.3704	0.0891
		RER	26.19%	9.24%	2.15%
	BP	AEV	1.6359	0.5995	0.1703
		RER	44.59%	14.95%	4.12%
Test 2	QT	AEV	0.5496	0.2159	0.1722
		RER	12.57%	5.16%	4.03%
	BP	AEV	0.6852	0.0497	0.2356
		RER	15.67%	1.19%	5.51%
Test 3	QT	AEV	0.1568	0.0712	0.0544
		RER	3.18%	1.83%	1.45%
	BP	AEV	0.2396	0.5181	0.0658
		RER	4.86%	13.30%	1.75%
Test 4	QT	AEV	0.7996	0.3947	0.0352
		RER	15.36%	9.22%	1.07%
	BP	AEV	0.7203	0.4298	0.3506
		RER	13.83%	10.04%	10.68%
	AgER-QT		14.32%	6.36%	2.17%
	AgER-BP		19.74%	9.87%	5.51%

Note: QT/ QTTI; BP/ BPNN; AEV/ Absolute error value; RER/ Relative error rate; AgER/ Average error rate

According to the table, the average error rate of perceptual vocabulary in various groups under the QTTI model are, 14.32%, 6.36%, and 2.17%, respectively; and the average error rates of the BPNN model are 19.74%, 9.87%, and 5.51%, respectively. Evidently, the QTTI model presents a better prediction effect.

5 Conclusions

Electric toothbrush samples and consumers' reviews on products were mined profoundly using web crawler and NLP. Then, SDS perceptual evaluation was performed on representative product samples and perceptual vocabulary extracted systematically. At the same time, modeling design elements of electric toothbrushes were deconstructed using the morphological analysis method and divided into 6 items and 25 categories, as shown in Table 1. Moreover, a correlation model between product modeling elements and user's perceptual image was constructed through QTTI multiple linear regression based on Kansei engineering, BPNN nonlinear analysis in combination with perceptual evaluation and product design elements for comparative analysis. This research can be concluded as below:

1. Online web crawler and NLP can improve the time-consuming data collection process in the early stage of Kansei engineering and provide effective and complete research data through extensively and deeply mining big data of product samples and consumer reviews.
2. Influences of various modeling items and categories on perceptual images:
   1) Influence of each item is ranked as: i. “Mature/Youthful”: toothbrush handle decoration> toothbrush handle > toothbrush head> toothbrush neck> Switch > connection of toothbrush neck and handle; ii. “Low-end/High-end”: toothbrush handle > toothbrush handle decoration> toothbrush head > toothbrush neck > connection of toothbrush neck and handle > switch; and iii. “Sophisticated/Minimalistic”: toothbrush handle decoration> toothbrush handle > connection of toothbrush neck and handle > toothbrush head > switch > toothbrush neck.
   2) In the ranking of the influence degree of various categories, take the “brush handle decoration” item in “Mature/Youthful” as an example: the scoring point of the “Youthful” image is ranked as cartoon decoration> ridged decoration> smooth and patternless surface, while the scoring point of the “Mature” image is ranked as dotted decoration>line stripe decoration.The rest can be analogized in the same manner (Table 3).
3. Application of QTTI, BPNN in the establishment of product perceptual prediction model is proven to be reliable in this study, and QTTI has better accuracy.

Systematic analysis method used in this paper is suitable for design application of product perceptual image modeling, which can provide designers with clear design indicators and improves for traditional black-box design. Meanwhile, GA-BPNN will be optimized with the introduction of intelligent algorithms in an attempt to study whether its prediction effect can be better than that of the QTTI model in the subsequent research.

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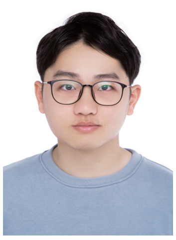

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