Deconstruction of product morphological features and multi-objective optimization in the context of multi-dimensional variable expression models

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Abstract. Consumers' perceptual images (PI) of products are multi-dimensional. Similarly, the stimulation of emotions by product is the result of the combined effect of multi-dimensional modeling features(MMF). However, in traditional Kansei engineering(TKE), most studies often use the one-dimensional variable expression model (OVEM) with only shape, color, or texture, and optimize product form based on a single PI objective. To address these issues, this paper proposes a method for deconstructing and multi-objective optimization of product morphological features based on a multi-dimensional variable expression model (MVEM). Firstly, the electric shaver is taken as a case, and the MMF library is constructed by deconstructing the morphological features of products from three levels: "appearance attributes," "interaction attributes" and "cultural attributes." Extract key design variables corresponding to multi-dimensional image needs(MIN) from the MMF library using link relative method. Then construct the prediction model of MIN separately using back-propagation neural network (BPNN) and it's embedded in the non-dominated sorting genetic algorithm-II (NSGA-II) to derive the Pareto optimal solution, which finally resulted in layouts of holistic multidimensional(HM) in Kansei engineering (KE). The research results demonstrate that the proposed construction process and methodology of HM are feasible and effective, with significant guidance and practical application value.

Keywords: Kansei engineering, Multi-dimensional variable, Product form design, Deconstruction method, Optimisation

1. Introduction

As market competition intensifies, product design is shifting towards a more consumer-centric approach. In the era of personalized consumption, consumers are placing greater emphasis on emotional reactions elicited by physical appearance when choosing products, rather than its functionality and usability [1]. The emotional response of consumers, which reflects their emotional needs, is receiving increasing attention. Kansei engineering (KE) [2, 3] is a methodology used to translate emotional responses to products into design elements, and has achieved significant success in the field of product design [4].

The traditional Kansei engineering (TKE) research process involves three key modules: extracting the modeling features (MF), acquisition of perceptual images (PI), and establishing a mapping model between the two [5]. For example, Woo et al. [6] used multi-dimensional scaling and hierarchical clustering analysis to extract design elements of electric toothbrush. They then established linear and non-linear models using quantification theory I (QTI) and back-propagation neural network (BPNN) respectively. Tsai et al. [7] established a quantitative relationship model between the styling features and representative descriptions of traditional headwear using fuzzy set theory (FST). Kang et al. [8] used Kansei engineering to extract users' emotional resonance with red

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culture, applied semiotics theory to extract design symbols of Jiangxi red architecture, and finally used interactive genetic algorithm (IGA) to construct an evolutionary design system for red cultural product forms. In these TKE applications, the MFs of the product are typically classified as "items" and "categories" using the morphological chart method [9]. This visualization structure simplifies the definition of product form variables, ultimately resulting in a one-dimensional variable expression mode (OVEM) for product shape. Furthermore, traditional methods are mainly focus on optimizing product form for a single target of PI [10], while in reality, and consumers often expect product designs that satisfy multiple PI targets.

From the perspective of multidimensional variable expression mode (MVEM), the MF of product and the user's PI are multidimensional and complex. A product's ability to evoke emotions in a user is the result of the combined influence of multidimensional modeling features (MMF), such as shape, color, and texture [11]. The OVEM based solely on shape [12], color [13], or texture [14] is insufficient for reliably predicting a product's emotional response. Han et al. [15] classify the design elements of a product that a user sees, touches, or uses, such as shape, color, size, and texture, as human interface elements (HIEs). Based on this, many scholars proposed multi-layered deconstruction methods for product form, and formulated design rules for MMF from a multi-sensory channel perspective [16, 17]. However, these studies just use multiple regression algorithms to establish KE models for user's multi-dimensional image needs (MIN). Yet, the results still convert the problem into single-objective optimization, leading to being stuck in a local multidimensional (LM) state and not fully meeting the user's MIN.

Consumers' PI needs for products are also multidimensional. When facing a complex product, users usually need multiple dimensions of image to express their dominant feelings [18]. Optimizing product form based on a single image objective in TKE obviously cannot satisfy consumers' MIN. In existing research, some researchers have noticed consumers' MIN [19, 20, 21], but they tend to use linear weighting or objective programming to transform them into a single objective for optimization, which can easily lose the optimal solution and lead to results that are no different from single-objective optimization. Other researchers have used multi-objective optimization algorithms to optimize the shape variables of products [22, 23], but they have overlooked the MMF such as color and texture, leading to their results also getting stuck in LM situations.

Consumers' emotions are multidimensional and cannot be adequately described using a single dimension. Similarly, consumers' emotions are often evoked by multiple dimensions and interaction design variables within the entire product. However, TKE research often focuses on a single aspect, resulting in an OVEM or LM expression, which makes it difficult to fully address the problem of multidimensional variable expression in KE. In response to the aforementioned problem, this study takes a holistic approach to explore the methods and processes for deconstructing product MF and performing multi-objective optimization under the MVEM. It constructs a multidimensional KE model that connects MMF and MIN, aiming to achieve a holistic multi-dimensional (HM) layout in the field of Kansei engineering that better meets the MINs of consumers facing complex products.

The remainder of this paper is organized as follows: Section 2 reviews the concept of HIEs, prediction model, and multi-objective evolutionary algorithm (MOEA). Section 3 presents the outline. Section 4 details the implementation procedures. Section 5 describes some discussions of the results. Finally, some brief conclusions are drawn in Section 6.

2. Literature review

2.1. The concept of HIEs

The perceptual qualities of a product, being intangible in nature, are inevitably conveyed and expressed during the interaction between individuals and the product. In this context, the human-machine interface serves as a crucial physical medium for transmitting perceptual information between humans and machines. Han et al. [15] refer to the collection of design features that users see, touch, or use in a product as the human interface elements (HIEs), which includes the most direct perceptual information about the product, such as its shape, color, material, and texture. In other words, the HIEs represent the smallest interface for information exchange between humans and machines, serving as the most elementary modeling units.

2.2. Model for prediction of emotional responses

Emotion prediction models are an important component in multi-dimensional KE. They enable the prediction of users' emotional responses, allowing for the evaluation of multiple alternative solutions. Additionally, these models serve as the foundation for executing MOEA. Emotion prediction models can be categorized into linear and non-linear. Commonly used linear models include Quantification Theory Type I [6], multiple regression analysis [24], and conjoint analysis [25]. These methods rely on the linear relationship between independent variables and dependent variables to guide the impact of MF on PI. However, these linear models often have low prediction accuracy [26].

In most cases, the relationship between MF and PI is not linear. As a result, many researchers have started using BPNN techniques in product design [27]. BPNN are information processing models developed to mimic the biological neural processing system and the unique learning and cognitive behaviors observed in humans. With its adaptability, non-linearity, and parallel computing capabilities, BPNN can continuously learn new knowledge and improve their own knowledge structures. It possesses inherent advantages in mapping and processing patterned knowledge. As a computational model based on simulating neural systems, BPNN technology offers more efficient, accurate, and scientific methods for emotion prediction. So it has wide-ranging applications in the field of KE and holds great potential in areas such as PI modeling.

2.3. Multi-objective evolutionary algorithm

To address the multi-dimensional response issues in product form design, there has been a growing interest in the application of MOEA in the field of KE. MOEA are search and optimization methods based on global probabilistic approaches. They are inspired by biological evolution mechanisms and can provide a Pareto set consisting of many optimal solutions [23]. Nowadays, the second-generation MOEAs, represented by non-dominated sorting genetic algorithm-II (NSGA-II), the Pareto envelope-based selection algorithm-II (PESA-II), and the strength Pareto evolutionary algorithm-2 (SPEA2), have improved their validation metrics compared to the first generation. The efficiency of these algorithms has also been significantly enhanced. Among them, NSGA-II is particularly widely applied in the field of KE and has become one of the benchmark algorithms in multi-objective optimization. NSGA was initially proposed by Srinivas et al. [28] in 1995, and later in 2002, Deb et al. [29] introduced an improved version of NSGA called NSGA-II. Shieh et al. [26] conducted a comparative study on three MOEAs: NSGA-II, PESA-II, and SPEA2. The results showed that NSGA-II provides the best performance in terms of convergence and a hybrid of convergence and diversity. Additionally, the application of NSGA-II generates a well-distributed set of Pareto solution, making it suitable for solving complex optimization problems in product form design.

3. Research framework

To construct a multidimensional KE model between MMF and MIN within the context of MVEM, the proposed implementation method and process of the HM layout, as shown in Figure 1, provide designers with a framework for achieving HM layout in product design. It mainly consists of the following three key components:

3.1. Acquisition of MMF and MIN

The preliminary stage of the research involves obtaining representative product samples and users' PI words. The process includes using cluster analysis to screen the product samples. Based on the selected samples, the Sensory Difference (SD) method is used to obtain the mean sensory evaluation of the products. Principal Component Analysis (PCA) is then applied to reduce the dimensionality and obtain representative PI words. Subsequently, the overall product HIEs deconstruction method is used to deconstruct the product MF into numerous multidimensional design variables. By employing a primary feature judgment process, the key design variables under each PI word are selected.

3.2. Constructing predictive models

The prediction models are constructed by utilizing the BPNN technique, considering the various product MMFs associated with each PI word. The procedure entails encoding the MMFs under each PI word and using them as input level data for the BPNN. The mean sensory evaluation is used as the output level data for the BPNN. The implicit layer of the BPNN is determined through trial and error, and the training process of the BPNN is conducted. The trained neural network model is saved for subsequent optimization work.

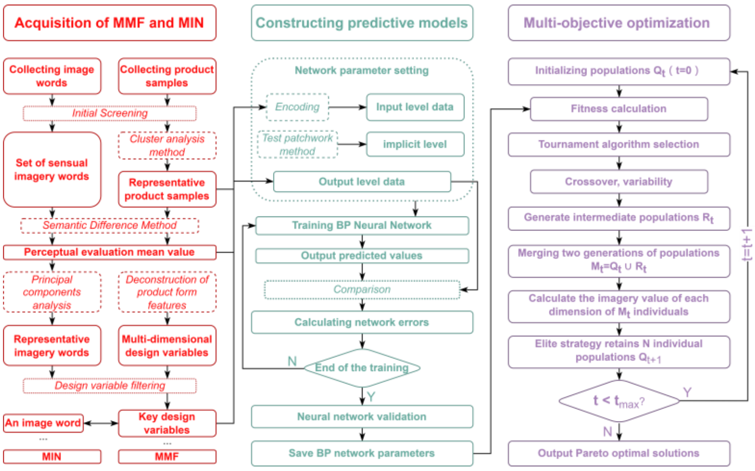

Fig.1. The implementation method framework of the proposed HM layout

3.3. Multi-objective optimization design

Finally, the NSGA-II is used to perform multi-objective optimization design of the product's multi-dimensional morphology. Through a series of algorithmic procedures, including population initialization, fitness function calculation, tournament selection, crossover operator, mutation operator, and pruning operation, the algorithm obtains a Pareto-optimal solution set of product shape optimization schemes that integrate multidimensional design features.

The proposed methods and procedures will be detailed and explained in the section 4, and the electric shaver is taken for the illustration purpose.

4. Implementation procedures

4.1. Constructing the sample library

4.1.1. Get the product modeling samples

We extensively collected the curent best-selling electric shaver images through online e-commerce platforms, electronic magazines, and official websites of brands. After removing unclear images, we obtained a total of 130 valid image samples. Next, we formed a focus group consisting of 20 postgraduate students specializing in industrial design. Based on the emotional responses evoked by the overall form of each image sample, we employed clustering techniques to classify samples with similar emotional connotations. The frequency of two images being assigned to the same group served as the basis for classification. Then, using a hierarchical clustering

Fig.2. Representative samples

approach, we retained the 20 electric shaver image that were closest to the cluster centers. To ensure the saccuracy of the selection results we invited five industrial design professors to examine the clustering process and outcomes. Finally, we used Photoshop to standardize the background and refine the details of the selected 20 electric shaver sample images, as shown in Figure 2.

4.1.2. Get the emotional vocabulary

By analyzing the product positioning reports from companies and consumer reviews related to electric shavers on e-commerce platforms, as well as reading relevant literature and books, we extensively collected descriptive vocabulary related to electric shavers and obtained 76 results. Then we eliminated words with similar meanings or low occurence frequencies and paired the remaining vocabulary with their respective antonyms. Finally, we have preliminarily identified 10 sets of representative PI words as our samples, as shown in Table 1.

Table 1
Representative perceptual vocabulary

Perceptual words	
Modern–Classical	Technological–Traditional
Streamlined–Stiff	Avant-garde–Conservative
Elegant–Vulgar	High-end–Cheap
Minimalistic–Complex	Soft–Harder-edged
Business–Casual	Distinctive–Ordinary

Table 2
Average value of perceptual evaluation

Sample No.	Modern–Classical	Technological–Traditional	Streamlined–Stiff	Avant-garde–Conservative	Elegant–Vulgar	⋮	Distinctive–Ordinary
1	0.79	0.76	0.43	0.74	0.7		0.65
2	0.53	0.57	0.36	0.61	0.32	⋮	0.55
3	0.64	0.62	0.67	0.49	0.69		0.35
…		…		…			…
19	0.31	0.24	0.34	0.21	0.16	⋮	0.27
20	0.33	0.31	0.49	0.37	0.46		0.34

Table 3
Total variance explained

Component	Variance explained before rotation			Variance explained after rotation		
	eigenvalues	% Of Variance	Cumulative %	eigenvalues	% Of Variance	Cumulative %
1	4.424	44.238	44.238	365.309	36.531	36.531
2	2.046	20.46	64.698	219.389	21.939	58.47
3	1.498	14.977	79.674	190.341	19.034	77.504
4	1.016	9.458	89.132	116.283	11.628	89.132
5	0.531	5.312	94.444			
…	…		…			
10	0.016	0.162	100			

Table 4
Factor loading coefficients after rotation

	Factor			
	1	2	3	4
Modern–Classical	0.867	0.345	-0.045	-0.078
Streamlined–Stiff	-0.182	0.162	0.879	-0.131
Elegant–Vulgar	-0.157	0.041	-0.231	0.534
Minimalistic–Complex	0.558	-0.305	0.35	0.92
Business–Casual	0.141	0.799	-0.209	-0.009
Technological–Traditional	0.923	0.517	-0.167	-0.03
Avant-garde–Conservative	0.808	0.236	-0.173	-0.059
High-end–Cheap	0.504	0.938	0.156	-0.039
Soft–Harder-edged	0.029	-0.335	0.909	-0.054
Distinctive–Ordinary	0.868	-0.013	0.034	0.007

4.2. PI assessments

We employed the SD method to assess the PI of the collected electric shaver samples. A questionnaire was created using a 7-level Likert scale, with positive values assigned to the words on the left side of each of the ten word pairs. We distributed the online questionnaire to a total of 100 respondents, including 70 adult males and 30 married females. Participants were asked to provide evaluations based on their subjective perceptions. We received 96 valid responses, which were then analyzed for questionnaire reliability using SPSS software. The *Cornbach's* α value was 0.941, indicating good reliability of the questionnaire. Finally, we computed the average perceptual evaluations of the representative samples, as shown in Table 2.

4.3. Principal component analysis

We chose PCA to reduce the dimensionality of the data and explain as much variance as possible using a small number of principal components. First, we performed KMO and Bartlett tests, the KMO validity analysis value was 0.872>0.5, and the significance P-value of Bartlett's spherical test was 0.000<0.05, indicating the presence of intercorrelations among the variables, and thus validating the suitability of conducting PCA. Next, we extracted common factors using PCA and calculated the contribution rates of the principal components in explaining the variables, the results are presented in Table 3. It can be observed that there are four eigenvalues greater than 1, and the cumulative contribution rate for variable explanation is 89.132, indicating that the four principal components contain a significant portion of the information from the correlated variables. Subsequently, we performed a varimax rotation to establish the correspondence between factors and research items, as shown in Table 4. Based on the data in the table, we selected the word pairs "technological–traditional," "Soft–Harder-edged," "high-end–cheap," and "Minimalistic–Complex" from the four principal components with the highest correlation values as the key vocabulary for our subsequent research.

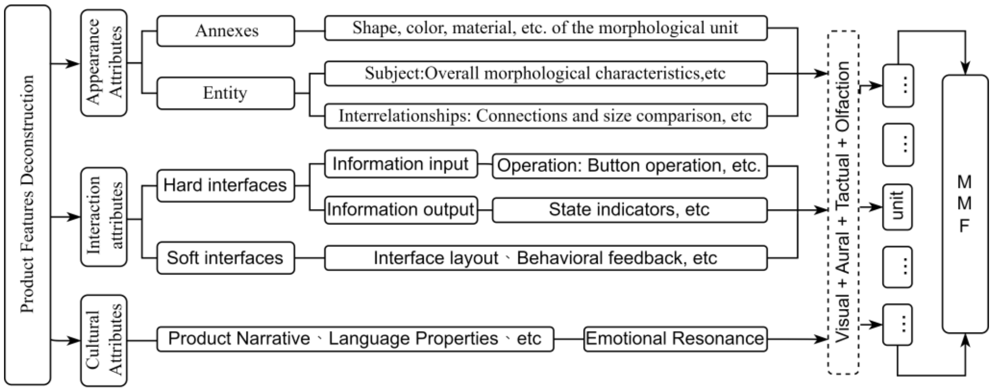

Fig.3. Framework for deconstructing product features

4.4. Construct MMFs space

4.4.1. Deconstruction of product MFs

The stimulation of user emotions by a product is the result of the combined effect of various dimensional design elements such as form, color, and texture. It also involves the interaction process of multiple sensory channels for users [30]. Therefore, it is not sufficient to use a single variable to express the MFs of a product. HIEs, as the smallest perceptual information units in the interaction between products and people, provide the foundation for deconstructing the MMFs of product. We have developed a set of deconstruction methods for the MMFs of products based on HIEs as the fundamental building blocks, and its framework is shown in Figure 3.

First, based on the HIEs units, we separate the MFs of the product into three deconstruction levels: "appearance attributes," "interaction attributes," and "cultural attributes." This allows us to systematically deconstruct the MMFs of the product.

Regarding the "appearance attributes," we primarily approach it from a visual perspective and divide the product's appearance into two parts: "annexes" and "entity." The term "annexes" refers to the MF of a particular morphological unit, including its shape, color, material, and texture. For example, the MFs of the electric shaver's head and the blade holder. The "entity" includes, on the one hand, the overall external features of the product, such as the contour, curvature, and chamfered edges of electric shaver. On the other hand, it includes the interrelationships between various components, such as the joining relationship and size proportion between two elements, and the composition relationship between individual components and the overall structure. The deconstruction of the "appearance attributes" of the electric shaver according to the above logic as shown in Table 5.

For the "interaction attributes," we approach it from the perspectives of visual, auditory, tactile, vibrational, and olfactory sensory channels. Based on different forms of interaction, we divide the product's interaction interface into two parts: "hard interface" and "soft interface." The extraction of the "hard interface" mainly focuses on functional components involved in information input and output. such as the switch button of the electric shaver for information input and the status indicator for information output. The extraction of the "soft interface" draws on the evaluation system of usability engineering and relies primarily on visual, tactile, and auditory sensory channels. It includes interaction logic information related to interface layout, logical sequence of operating systems, and graphical relationships within product components. For example, the arrangement of the operating interface and the intensity of button feedback. Following this logic, we have deconstructed the "interaction attributes" of the electric shaver, and the results are shown in Table 6.

For the "cultural attributes," we define it as the subdivision of HIEs from the perspective of "language or symbol attributes." It involves analyzing the cultural connotations and product narratives embedded in the product, and integrating the cultural dimension to explore the emotional resonance generated by users towards different cultural symbols. This logic is particularly applicable to culturally creative products. However, since the focus of this research is on electric shavers, which belong to the category of small home appliances and smart products, the emphasis on "cultural symbols" attributes is not highlighted. Therefore, it is not included in the scope of consideration.

Table 5
Feature deconstruction of product "appearance attributes"

	Category	NO.	HIEs
Annexes	Blade head	1	A_1 Shape of blades
		2	A_2 Number of blades
	Blade holder	3	B_1 Curvature of the side edge of the blade holder
		4	B_2 Curvature of the bottom edge of the blade holder
		5	B_3 Color of the blade holder
		6	B_4 Texture of the blade holder
	Handle	7	C_1 Color of the handle
		8	C_2 Material of the handle
		9	C_3 Anti-slip texture of the handle
Entity	Subject	10	D_1 Curvature of the body side curve
		11	D_2 Rounding of the bottom chamfer of the body
		12	D_3 Material texture of the body
		13	D_4 Color brightness of the body
		14	D_5 Number of colors of the body
		15	D_6 Size of the body color area
		16	D_7 Number of body divider lines
	Interrelationships	17	E_1 Connection formbetween the head and body (neck)
		18	E_2 Transition area for neck connection
		19	E_3 Curvature of the transition edge line of the neck
		20	E_4 Uniform color of the neck connection
		21	E_5 Curvature of the joint line between the blade holder and head
		22	E_6 Uniform Color of the transition area between the blade holder and head
		23	E_7 Curvature of the joint line between the handle and body
		24	E_8 Head to body aspect ratio
		25	E_9 Percentage of colored area
		26	E_{10} Proportion of primary and secondary colors

Table 6
Feature deconstruction of product "interaction attributes"

	Category	NO.	HIEs
Hard interface	Information input	27	F_1 Shape of switch key
		28	F_2 Color of switch key
		29	F_3 Texture of switch key
		30	F_4 Touch texture of switch key
		31	F_5 Scale share of switch key
		32	F_6 Position height of switch key
		33	F_7 Form of use the switch key
		34	F_8 Shape of control panel
		35	F_9 Layout of control panel
		36	F_{10} Area share of control panel
		37	F_{11} Control panel colors
	Information output	38	G_1 Power indicator
		39	G_2 Working status indicator
Soft interface	Visual	40	H_1 Color of indicator icon
		41	H_2 Size of indicator icon
		42	H_3 Brightness of indicator icon
		43	H_4 Location of indicator icon
	Haptics	44	I_1 Sensitivity of switch key
		45	I_2 Feedack strength of switch key
	Aural	46	J_1 Beep for switching on and off
		47	J_2 Feedback sound of key presses
		48	J_3 Feedback sound for mode switching
		49	J_4 Razor working state sound effects

4.4.2. Identification of the major features of MMFs

After conducting a multidimensional feature deconstruction of the product modeling, we obtained 49 HIEs for the electric shaver. However, not every MFs has an impact on the user's emotions, and the degree of influence of the same MF can vary for different emotional targets[16].Therefore, we next need to identify the importance of MMFs of the electric shaver to determine the key features that hold higher importance for each emotional target. To achieve this, we have chosen the Link Relative Method for comparing the MFs. This method is a variation of the numerical estimation method proposed by Steven, S.S. in the 1950s, which converts subjective judgments into sensory amount. It is one of the commonly used fuzzy ranking methods in psychology. Moreover, the core of this study is to explore the influence of MMF on users' psychological experiences, which involves the intersection of product design and psychology. Therefore, the Link Relative Method is suitable for us to judge the main features of MMFs.

We take the 10 design elements E_1–E_{10} of the "interrelationship" in Table 5 as an example to illustrate the process of using the link relative method, the main steps are as follows:

- Step 1: Invite 3 professors specializing in human-computer interface design and 3 professors specializing in industrial design, totaling 6 participants. Use the "technological" as the emotional target from the four sets of sensory words. Choose design element E_1 with moderate intensity from the 10 design elements as the standard stimulus and assign it a sensory amount value of 1.
- Step 2: Perform link comparisons for the remaining 9 design elements, as shown in Table 7. The test participants compare each variable with its adjacent variable, starting with E1. For example, compare E2 with E1, then compare E3 with E2, and so on. Simultaneously, record the proportion of sensory amount triggered by each variable compared to its adjacent variable. Through this process, the importance ratio can be sequentially adjusted.
- Step 3: Calculate the sensory amount for each design element. The sensory amount of each element is obtained by multiplying the sensory amount of the adjacent variable by the importance ratio of that element. For example, multiplying the sensory amount of E_1 by 0.8 gives the sensory value of E_2 as 0.8. Using this method, calculate the sensory amount for the 10 design variables in this category. Additionally, using the standard stimulus variable E_1 as a baseline, the design elements with sensory amount greater than or equal to E_1 are considered as key design features in the "technological" emotional target for the interrelationship category of the electric shaver.

Based on the above logic, calculate the key design features that have a higher impact for each set of sensory words. Determine the specific types included in each key design feature with the assistance of the professors. The results are presented in Table 8.

Table 7
Main features judgment

Variables	Multiple	Sensory amount
E_1	–	1
E_2	0.8	0.8
E_3	0.5	0.4
E_4	2	0.8
E_5	0.3	0.24
E_6	1.2	0.288
E_7	1	0.288
E_8	2	0.576
E_9	2	1.152
E_{10}	0.7	0.8064

Table 8
Key design variables under each perceptual vocabulary

Perceptual words	Key features	Level	Type	Perceptual words	Key features	Level	Type
	A_1	2	Flat/Round		A_2	4	1/2/3/5
	A_2	4	1/2/3/5		D_1	3	Radius of curvature large/medium/small
	D_3	2	Metal/Plastic		D_3	2	Metal/Plastic
technological–traditional	E_1	4	Fine/medium/coarse/none	high-end–cheap	E_4	2	Yes/No
	E_9	4	>80%/80%-20%/<20%/0		E_{10}	3	>0.9/0.9-0.7/0.7-0.5
	F_7	2	Sliding/Key		E_9	4	>80%/80%-20%/<20%/0
	G_2	2	Yes/No		F_1	2	Round / Rectangular
	J_1	2	Yes/No		F_3	2	Metal/Plastic
	J_3	2	Yes/No		H_2	3	Large/small/none
	A_1	2	Flat/Round		A_2	4	1/2/3/5
	B_1	3	Radius of curvature large/medium/small		C_3	3	Striped/dot matrix/no
	D_1	3	Radius of curvature large/medium/small		D_5	2	2/3
Soft–Harder-edged	D_2	2	Smooth/Steep	Minimalistic–Complex	D_7	3	More/Medium/Less
	D_4	3	High/Medium/Low		E_1	4	Fine/medium/coarse/none
	E_7	3	Radius of curvature large/medium/small		E_4	2	Yes/No
	E_9	4	>80%/80%-20%/<20%/0		E_6	2	Yes/No
	F_1	2	Round/Rectangular		F_{10}	3	Large/Medium/Small
	J_4	2	Strong and soft				

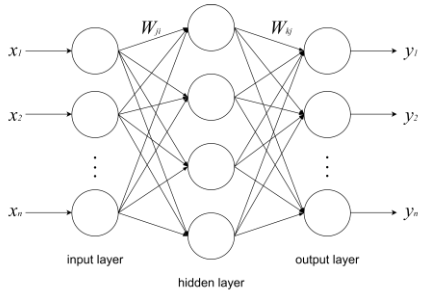

Fig.4. Structural model for BPNN

4.5. Construction of BPNN prediction models

The relationship between emotional responses and the morphological variables of a product is often highly nonlinear[17]. In this study, we chose to use BPNN technique to address this nonlinear problem. BPNN is a multilayer feedforward network trained using the error backpropagation algorithm. It has the ability to learn and store a large number of input-output pattern mappings, making it well-suited for describing nonlinear relationships between variables and targets[31]. The structure of BPNN typically consists of input layer, output layer and hidden layer, as shown in Figure 4. The network training process involves two steps: forward propagation of signals and backward propagation of errors. By iteratively performing these two steps and continuously adjusting the weights of the hidden layers, a neural network model that meets the training requirements is eventually produced.

4.5.1. Parameter setting for BPNN

Based on the aforementioned study, we have obtained four sets of perceptual words and their key morphological features. In order to facilitate the subsequent multi-objective optimization work of this study, it is necessary to construct separate BPNN models for each set of perceptual words. Before conducting the network training of BPNN, the parameters of its layers need to be set. Therefore, we take the perceptual word pair "technological-traditional" as an example to explain the method of setting parameters for the input layer, output layer, and hidden layer of BPNN.

Input layer

Using the 20 samples from the electric shaver's morphology sample library as training samples. Assuming that each training sample contains m morphological features. In the x sample, each morphological feature consists of n types, there are a total of $P=\sum_{j=1}^{m} n$ types, and $y_x=\delta_x(i,j)(i=1,2,\cdots,m$ $;j=1,2,\cdots,n)$ represent the impact of the j type of the i morphological feature in the x sample on the target, determined according to Equation (1):

$$\delta_x(i,j)=\begin{cases}1 & \text{The } i \text{ morphological feature in the } x \text{ sample is of type } j \\ 0 & \text{Others}\end{cases} \tag{1}$$

For example, in the 20th sample, there are a total of 9 morphological features, including 24 related types. According to Equation (1), we can determine the presence of these 24 attributes in the sample, and obtain its parameter encoding as $\delta_x(i,j)=(01010001\ 1000000101101010)$.

By following the aforementioned method, we can obtain the encoding for each of the 20 samples under the "technological-traditional" perceptual imagery. This allows us to parameterize the MMFs of the training samples and use them as input data for constructing the BPNN model.

Hidden layer

Based on the previous information, we have determined that under the "technological-traditional" perceptual imagery, there are 9 MMFs with 24 associated types. Therefore, the input layer of the BPNN model will have 24 nodes, and the output layer will have 1 node. According to Equation (2), we calculate the range of the number of neurons in the hidden layer to be $p \le 9$. Then, using trial and error method, we can determine the specific value. This involves testing the results for each value and selecting the one that corresponds to the best outcome while meeting the required accuracy. Through successive experiments, we found that around 5 neurons in the hidden layer are the most suitable, as they result in the lowest output error for the network structure.

$$p \le \sqrt{l \times (q+3)} \tag{2}$$

where p is the number of nodes in the hidden layer; l is the number of nodes in the input layer; and q is the number of nodes in the output layer.

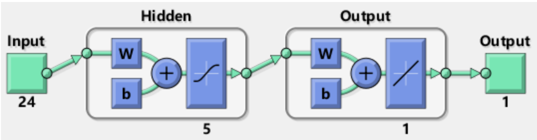

Fig.5. The BPNN structure for "technological-traditional"

Output layer

Use the mean values of perceptual evaluation for "technological-traditional" in Table 2 as the output layer data of the BPNN model.

By setting the parameters, the final BPNN model structure for the "technological-traditional" is obtained with 24 nodes in the input layer, 4 nodes in the hidden layer, and 1 node in the output layer, as shown in Figure 5. Following the same method, we determine the BPNN model parameters for the other three perceptual categories as well.

4.5.2. Training of BPNN model

Based on the BPNN model parameters for each group of perceptual words, we will use the Matlab R2020b platform to construct four groups of BPNN models respectively. The input data for each model was the encoding of the corresponding set of MMFs, and the output data was the average sensory evaluation values of the training samples. We set the Log-sigmoid function as the activation function and the Purelin function as the transfer function. The desired error goal was set to 0.01, and the mean squared error (MSE) between the predicted values and the actual values was used as the measure of model accuracy. The BPNN models were trained using the Trainlm optimization algorithm, and the training results are shown in Figure 6. Based on the training results, it can be concluded that all four sets of BPNN models have achieved their respective training objectives. Additionally, the best error performances in all models meet the requirements for training errors. This preliminary analysis indicates that the four BPNN models exhibit good accuracy and feasibility.

4.5.3. Testing of BPNN model

In order to effectively assess the prediction accuracy of the BPNN models, we have employed the leave-one-out cross-validation method to test the four models. The traditional testing approach involves splitting the dataset into training and testing samples. However, due to the limited number of samples in this study, using the traditional method would result in insufficient training data, thereby compromising the model's generalization ability. Therefore, we have adopted the leave-one-out cross-validation method, where each of the 20 samples in the dataset is used as a prediction sample. By conducting 20 rounds of cross-validation, we obtain the sensory prediction values for each sample, ensuring the optimal utilization of the sample data. By calculating the relative error between the predicted values generated by the models and the actual perceptual averages, we have completed individual tests for the four groups of BPNN models. The test results indicate that the relative errors between the predicted and actual values are small, further validating the effectiveness and high accuracy of the four BPNN models. Consequently, these models can be applied in subsequent multi-objective optimization tasks.

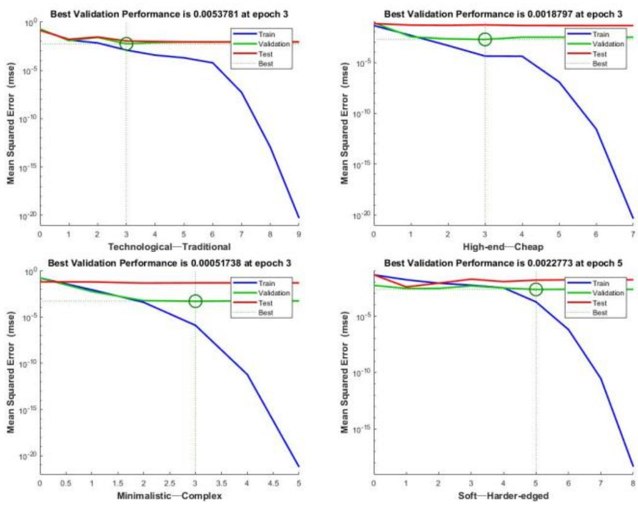

Fig.6. Results of BPNN model training

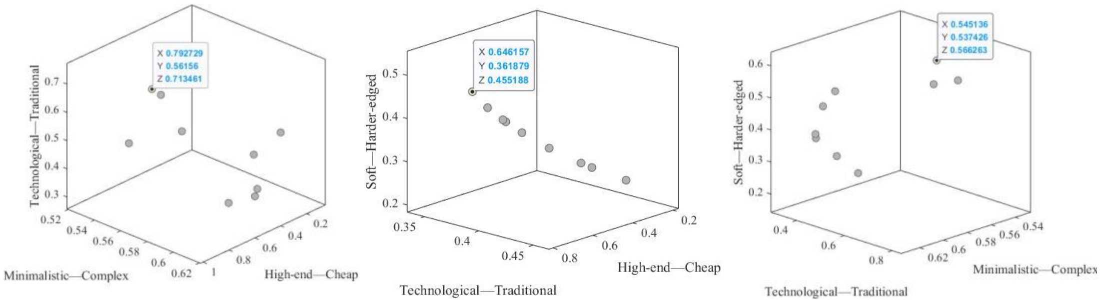

Fig.7. Pareto solution set distribution for multi-objective optimization

4.6. Multi-objective optimization

In order to achieve multi-objective optimization design of electric shavers in a multidimensional variable expression mode, we employed the NSGA-II algorithm for finding the optimal Pareto solutions. This process was implemented using the Matlab R2020b platform, where the BPNN function code was used as the objective function to calculate the fitness values of generated solutions. The initial population was set to 50, with a single-point crossover probability of 0.8 and a uniform mutation probability of 0.1. The termination generation for the algorithm was set to 500. After 500 iterations, we obtained the distribution of Pareto optimal solutions, as shown in Figure 7. The solution set consists of 10 non-inferior solutions, and these solutions are evenly distributed in the three-dimensional space, indicating that the obtained solution set can satisfy various different requirements. Furthermore, each solution in the Pareto optimal set can be considered as the best result. Enterprises or design teams can comprehensively consider consumers' different dimensions of perceptual needs and select suitable solutions from the non-inferior set based on the combination of multidimensional design variables corresponding to each non-inferior solution. This enables further research and development, and production based on the selected solutions. If a stronger emphasis is placed on the "technological" factor among the four perceptual dimensions, the larger solution associated with the "technological" factor can be chosen, while other perceptual factors can be selected using the same method.

5. Discussion

5.1. Multi-dimensional design variables in multi-dimensional imagery

During the initial stage of the research, we collected data on the modeling and perceptual aspects of electric shavers. Using SD mothod, we established the evaluation relationship between the two. Based on the evaluation results, we conducted dimensionality reduction using PCA to obtain four representative groups of perceptual words. This successful outcome signifies that we have effectively captured the MIN of consumers regarding electric shavers.

Using the HIEs as the minimal information unit, we comprehensively deconstructed the MFs of electric shavers from different dimensions. This process resulted in a MMF library consisting of 49 feature units. Since the impact of product MF varies across different PI, it is inappropriate to use the same set of design variables for multiple perceptual objectives. Therefore, we employed the link-relative method to extract different key design variables for each PI from the MMF library. Through this approach, we successfully obtained the multidimensional design variables that have a significant influence on each PI. This method allows for a more scientific establishment of the relationship between MF and PI.

5.2. Multi-objective optimization of multidimensional imagery

To optimize the four groups of multidimensional imagery objetives, and explore the Pareto optimal solutions for product form design that integrates MINs and MMFs. We first constructed separate predictive models for each group of PI using the BPNN technique and successfully verified the accuracy of the four sets of BPNN models using the leave-one-out cross-validation method. We saved the function codes of the four BPNN models during this process, allowing us to use them as objective functions in the NSGA-II algorithm for multi-objective optimization. By programming and setting the parameters of NSGA-II using Matlab R2020b, we successfully completed the multi-objective optimization of the four groups of PI and their design variables. The results demonstrate a relatively even distribution of non-inferior solutions, enabling us to select suitable solutions from the solution set to meet various requirements. Moreover, each optimal solution corresponds to a combination of design variables for different PI.

6. Conclusion

This study deconstructed the MMF of a product by analyzing it from multiple dimensions. The NSGA-II algorithm was then employed for multi-objective optimization, aiming to integrate MIN and MMF to seek the optimal solution for product form design. This approach established a HM layout in the field of Kansei engineering. The feasibility of this method was demonstrated through a case study using an electric shaver, and it can also be applied to the design of other products. The following conclusions were drawn:

(1) The analysis of experimental results indicated that the deconstruction method of product morphological features, which integrates “appearance attributes” and “interaction attributes” based on the minimal information unit HIEs, is applicable to Kansei research. This method aligns with the principles of product form design and enhances the practical value of Kansei engineering models.

(2) The NSGA-II multi-objective optimization algorithm can effectively be used to seek the optimal solution for the combination of MIN and MMF. It provides the possibility of achieving a HM layout. By analyzing the combinations of different multidimensional design variables in the optimal solution, the designed product can better align with the users' multidimensional aesthetic requirements.

(3) The research results demonstrate the feasibility of our proposed HM layout in the field of Kansei engineering. The construction process based on the deconstruction of multidimensional morphological features and the optimization of multiple image objectives is scientifically effective. This HM Kansei engineering system can better fulfill consumers’ complex imagery demands.

It should be noted that in this study, the influence of cultural attributes on consumers’ PI was not considered. Future research could focus on selecting appropriate cultural products to explore the relationship between cultural elements within a product and users’ emotional responses. Additionally, while we utilized the BPNN algorithm to construct predictive models between PI and MF, other algorithms such as SVR can also effectively establish nonlinear models. With the continuous improvement and upgrading of algorithms, more effective algorithms and optimization methods can be introduced in future work to enhance the usability of the whole design method as well as the speed of optimization.

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