Research Article

Target Mining and Recognition of Product Form Innovation Design Based on Image Word Similarity Model

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Product Kansei image design is one of the research hotspot of product emotional design. Due to the subjectivity, low efficiency, and low level of intelligence in the existing product form innovation design methods in the mining of design goals. This study combines the semantic dictionary of Tongyici Cilin with Kansei engineering theory and uses clustering analysis algorithm, semantic difference method, and word similarity calculation method to realize product Kansei image design. Tongyici Cilin is a computable Chinese semantic dictionary. In this study, we innovatively introduced Tongyici Cilin into the image word similarity calculation in product image design. First, the product image design process based on Tongyici Cilin is proposed. Then, we establish a model of image word similarity calculation using the common distance, difference distance, common adjustment parameter, and differential adjustment parameter. By comparing with international standard data, it is confirmed that the image word similarity calculation model proposed in this article is effective and efficient. Using the sedan image design of middle-aged, middle-income men as an example, the sedan form style of each target image was successfully derived from the Internet-based questionnaire. Based on the case studies, we determined that it is effective to use the Tongyici Cilin semantic dictionary to determine the target image and improve the efficiency of product image design.

1. Introduction

With the rapid development of modern technology and the continuous upgrading of products, it is often difficult for the functions of products to surpass the competition. Consequently, the emotional design of a product becomes the decisive factor for consumers considering purchasing the product [1]. The development of manufacturing and information industry makes people pay more attention to their emotional needs while they experience material results and they also hope that products can reflect their personality, preferences, and values [2]. Intelligent design involves applying modern information technology, using computer simulations of human thinking activities, and improving the intelligence levels of computers so that computers can more successfully undertake complex tasks in the design process and thereby become an

important auxiliary tool for designers [3]. Using intelligent design technology can also increase the efficiency of product emotional design.

In order to better understand the emotional needs of users, some scholars have used the method of Kansei engineering [4] to explore the user's emotional factors. Japan's Nagamachi M. defines Kansei engineering as the technique of translating people's imagination and sensibility into physical design elements, and specifically carrying out product development and design. In short, Kansei engineering is to study the relationship between human emotions and product design elements and to apply consumers' emotional expectations to design products that meet consumers' emotional needs [5].

Generally, products can be divided into three levels: core products, formal products, and extended products [6]. The core products are the utility and benefits provided to consumers by

the product as a whole. The formal products are the physical appearance of the product in the market, including product shape, color, trademark, and packaging. The extended products refer to a series of additional functions provided to customers by the overall product, such as delivery, installation, and maintenance. This article focuses on the product form innovation design from the formal products.

Kansei words or Kansei image words are usually used to express people's preference of product form in Kansei engineering. As the basic unit of thinking, a Kansei image is the physical memory and overall impression formed by the processing of appearance information in the cognitive thinking space [7]. The appearance information refers to the people's perception of the object. After that, the product Kansei image is the communication language that emerges from people's perceptions of the product's form, color, and texture based on memory, experience, and associations. Product form or product modeling is the most direct way to reflect product-related emotions. In product Kansei image design, Kansei image-describing words such as "graceful," "handsome," and "streamlined" are usually used to express overall feelings of product form. Some studies call Kansei engineering as perceptual engineering, and product Kansei image design as product perceptual image design or product image design. Therefore, the above concepts are consistent in the field of product innovation design.

At present, product Kansei image design is one of the research hotspot for industrial design. Experts and scholars have conducted related research in bicycle saddle design [8], automobile design [9–14], financial equipment design [15, 16], sports shoes design [17], electric motorcycle design [18], and electric scooter design [19].

Hartono [20] used Kansei engineering to study the lounge and lobby services of international airports to clarify the emotional needs of customers. Zabotto et al. [21] established a Kansei engineering system based on rough set probability statistics in order to capture user's opinions during product design. Qiu et al. [22] used fuzzy entropy to evaluate the cognitive friction between designers and users, combined with the game theory to establish a cognitive friction balance model, to design the product's Kansei image. Wu et al. [23] used the back-propagation neural network of the gray model to construct a green-initiative Kansei engineering system to clarify people's sustainable perception of things. Zhang and Yang [24] combine the ontology to mine the user's color image of product modeling and apply it to the process of color image recognition. Xue et al. [25] applied Kansei engineering theory to construct a comprehensive decision-making system for product image design and applied it to the design of listed seats. Du et al. [26] proposed a semantic-based retrieval method for product design inspiration sources to help designers obtain design inspiration in conceptual design. Liu and Tong [27] use Kansei engineering and the gray relational analysis method to realize the product development and design process, thereby building the relationship between customer needs and product elements. However, these research methods did not conduct systematic and comprehensive research on the determination of design goals in product Kansei image design.

The goal mining of product form innovation design is to determine the goal image words of product image design,

which can be done through the methods of subjective evaluation [28], frequency statistics, and mathematical statistical analysis.

The subjective evaluation method is used to select a certain number of image words from the image word collection as the target image words according to the designer's own experience and knowledge.

The frequency statistics method is considered as the basis of determining the target Kansei image words by using the frequency of image word selection for different subjects. For example, [29] collected 76 image words and 63 product pictures for Train's Interior Form. Then, 67 subjects were asked to use the product pictures to represent the above image words or vice versa. 126 pairs resulted, and 56 pairs remained after a preliminary screening. Next, 60 college students were asked to select 28 pairs of image words from 56 pairs of words that best matched their visual perception. Finally, the selection results were counted, the image words selected more than 20 times (1/3) were retained, and 17 sets of image words were determined for the target images.

The mathematical and statistical analysis to determine the target image was achieved using principal component analysis or cluster analysis combined. For example, [30] extracted 128 image words for bus style based on customers' natural language. Then, 19 image words were initially selected as the reference words for the description of passenger cars through a statistical analysis of the 376 questionnaires collected. Next, the semantic scale of the image word was divided by using a Richter 7-point scale experiment. Finally, the SPSS (Statistical Product and Service Solutions) software was used to complete the principal component analysis to reduce the 19 image words into seven image words for the target images.

Determining the target images is a key step in product image design, which is very important for product emotional design. At the same time, the target images also determine the direction of product form innovation designs. However, the existing methods for determining the target images have several shortcomings. First, the subjective evaluation method uses subjective evaluation based on the subjects' perceptions of the product, which have certain subjectivity and limitations. Second, frequency statistics and mathematical statistical analysis methods have many steps, heavy workloads, and complex programs [29, 30]. To simplify the process of determining the target images, reduce the complexity of data processing, and avoid errors caused by subjective factors, we introduce a new method that uses Tongyici Cilin semantic dictionary to determine the target images for product Kansei image design. Tongyici Cilin comes from the Information Retrieval Research Center of Harbin Institute of Technology and has certain universality and extensiveness in Chinese processing.

Word similarity calculations are widely used in natural language processing, intelligent retrieval [31], text classification, data mining [32], and automatic responses. Such methods are a basic subject of natural language research. Word similarity calculations based on a semantic dictionary are one of the methods for determining word similarity. Commonly used semantic dictionaries for English words include WordNet, FrameNet, and MindNet, while those for Chinese words include Tongyici Cilin, HowNet, and the Chinese Concept Dictionary

[33]. Zhu et al. [34] proposed a text classification method based on the dependencies and the Tongyici Cilin semantic dictionary. Recent studies have shown that the internal composition of the Chinese word provides rich semantic information for Chinese word representation [35]. Chinese characters have semantic information. However, these methods of word similarity calculation based on Tongyici Cilin have not been studied in product Kansei image design, and the accuracy of existing word similarity calculation methods needs to be improved.

This paper first proposes a product image design process based on Tongyici Cilin semantic dictionary. Second, the calculation method for image word similarities is studied by using the arrangement and semantic characteristics of Tongyici Cilin. Then, an image word similarity calculation model is constructed by applying the common distance, the difference distance, the common adjustment parameter, and the difference adjustment parameter. Finally, according to the product image design process, a case study for middle-aged, middle-income men's sedan image design is operated.

The main contributions of this research involve

- (1) Propose a method for mining design goals in product form innovation design based on word similarity calculation
- (2) The calculation of word similarity is introduced into Kansei engineering and product modeling innovation design
- (3) This study improves the accuracy, objectivity, and efficiency of mining the design goals of product form innovation

The organization of this article is as follows. Section 2 describes the methods while Section 3 introduces the case study. Section 4 shows the results. Finally, the discussion and conclusion are presented in Section 5 and Section 6, respectively.

2. Method

2.1. The Product Image Design Process Based on the Tongyici Cilin Semantic Dictionary. As shown in Figure 1, the product image design process based on the Tongyici Cilin semantic dictionary includes five stages: determining the design task, collecting image words and product samples, determining the target images, determining the research samples, and determining product's form image style.

Step 1. Determining the design task. The first step of product image design is demand analysis [36], problem characterization [37], and task determination according to the target of the product design. Demand analysis entails a preliminary analysis of the design requirements for product image design. The problem characterization involves summarizing and expressing the design requirements, and task determination involves determining the final design requirements, such as target user group, target product, target user group characteristics, target product characteristics, and constraints.

Step 2. Collecting image words and product samples. To collect image words, first, it is necessary to mine image words that can express product form on the Internet, in product advertising, etc. Then, the designer filters and supplements the image words collected on the network platform. Finally, an image word set is produced, and the target image words are later derived from the image word set. To acquire product samples, network resources are employed to collect pictures of target products as the samples. Product samples need to have a consistent perspective and background to eliminate the image evaluation errors. Product image design requires image evaluation based on the study samples to clarify the product form styles for different image. The research samples come from a collection of product samples determined by screening and supplementing the collected product samples of the designers.

Step 3. Determining the target images. The target images of the product image design refer to a certain number of words in the image word set. Similarity calculation and cluster analyses were used to determine the target images of the product image design in this paper. Similarity calculation include the matching of the image words with the Tongyici Cilin database, calculating image word similarities based on Tongyici Cilin, and generating image word similarity data. Cluster analysis includes setting the cluster analysis parameter and performing a significance test. If the number of target imagery for product imagery design is n . The initial image word set is then divided into n categories through a similarity calculation and cluster analysis.

Step 4. Determining the research samples. If the number of research samples is too large, the research samples cannot be used to conduct an effective target image cognitive evaluation survey. The method used to determine the study sample was to select a specific number of product pictures from the product sample picture set. Usually, the research samples are determined by the designer through a comparative analysis to ensure that the number of research samples is moderate.

Step 5. Determining product's form image style. The establishment of the questionnaire involves using Internet technology to establish a product image design network questionnaire for the target images and research samples. According to the statistical data of the questionnaire, the corresponding relationship between the target image words and the research samples can be obtained. Further, the product form style of the target images can be clarified, and the product image design can be realized through the product form style.

2.2. Image Word Similarity Calculation Based on Tongyici Cilin Semantic Dictionary

2.2.1. Encoding Rules of Tongyici Cilin Semantic Dictionary. Tongyici Cilin is a computable Chinese thesaurus compiled by Mei [38], which initially realized the classification of synonyms and similar words. This article adopts the "HIT Information Retrieval Laboratory Tongyici Cilin Extended Edition" (Tongyici Cilin or Cilin for short), which was expanded by

FIGURE 1: The product image form design process based on the Tongyici Cilin semantic dictionary.

the Information Retrieval Research Center of Harbin Institute of Technology based on the computable Chinese lexicon.

As shown in Figure 2, Tongyici Cilin divides words into five types, including 12 major categories, 95 medium categories, 1428 small categories, 4026 word groups, and 17,797 atomic word groups (Che et al. 2010). The 1st–4th layers

of Cilin represent the abstract categories without specific headwords or concepts, and the fifth layer represents specific headwords or concepts. Each word has an 8-bit code in Tongyici Cilin. The 1st–7th bits are an uppercase letter, a lowercase letter, two digits, an uppercase letter, and two integers, respectively. The eighth bit is represented by “=,” “#,” or

FIGURE 2: Schematic diagram of the tree structure of the Tongyici Cilin semantic dictionary.

“@.” “=” indicates that the words have the same meaning in the atomic word group, “#” indicates that the words have similar meanings in the atomic word group, and “@” indicates that the word’s meaning is independent in the atomic word group [39].

It can be seen that the coding and path of the image word can be clarified through the tree structure of the Tongyici Cilin semantic dictionary. In addition, the coding and path information of the Tongyici Cilin implies the similarity information of the image words. This information actually comes from the editor of Tongyici Cilin and is determined by the coding rules of Tongyici Cilin. When calculating the similarity of image words, if we can accurately analyze the rich information contained therein and transform it into a computer executable algorithm after formalizing it, we can calculate the similarity value between two image words based on Tongyici Cilin.

2.2.2. Constructing an Image Word Similarity Calculation Model. This paper introduces Tongyici Cilin into the calculations of image word similarities. The image word similarity calculation model is based on common distance, difference distance, common adjustment parameter, and differential adjustment parameter, which improves the accuracy and efficiency of word similarity calculations. This method also provides a research foundation for determining the target images and provides technical support for intelligent product design research in product image design. Image word similarity is expressed as a number with a range of [0, 1]. This similarity relates to the commonalities and differences between image words. The greater the commonalities, the greater the similarity, and the greater the differences, the poorer the similarity. As shown in Figure 3, k represents the number of nodes of the two image words from the root node O to the nearest public parent node K . j represents the number of nodes from the nearest public parent node K to the location of the image word, and $k + j = 5$. According

to Figure 3, the similarity of image words includes a common part and a different part. In Tongyici Cilin, if the encoding of two image words is the same in the k -th layer, then the nearest common parent node of the two image words is in the k -th layer.

Definition 1. If the two image words are y_1 and y_2 , the commonality and difference between y_1 and y_2 are $g(y_1, y_2)$ and $c(y_1, y_2)$, and the similarity $\text{sim}(y_1, y_2)$ between y_1 and y_2 is defined as

$$\text{sim}(y_1, y_2) = \frac{g(y_1, y_2)}{g(y_1, y_2) + c(y_1, y_2)}. \quad (1)$$

Definition 2. The common distance between the two image words y_1 and y_2 is defined as the distance from the root node O of the word to the nearest common parent node K , which includes the distance $L_{g1}(y_1, y_2)$ from the root node O to the nearest common parent node K of the y_1 image word and the distance $L_{g2}(y_1, y_2)$ from the root node O to the nearest common parent node K of the y_2 image word.

Definition 3. The difference distance between the two image words of y_1 and y_2 is defined as the sum of the distances from the nearest common parent node K of y_1 and y_2 to the image words of y_1 and y_2 , respectively, which includes the distance $L_{c1}(y_1, y_2)$ from the nearest common parent node K to the y_1 image word and the distance $L_{c2}(y_1, y_2)$ from the nearest common parent node K to the y_2 image word.

Definition 4. The commonality $g(y_1, y_2)$ of the two image words y_1 and y_2 is defined as the sum of the common distance and the common adjustment parameter. If the common adjustment parameter of the image word similarity is α , then

FIGURE 3: Path of two image words in the Tongyici Cilin semantic dictionary.

$$g(y_1, y_2) = L_{g1}(y_1, y_2) + L_{g2}(y_1, y_2) + \alpha, \quad (2)$$

$$\therefore L_{g1}(y_1, y_2) = L_{g2}(y_1, y_2). \quad (3)$$

Next, set $L_g(y_1, y_2) = L_{g1}(y_1, y_2) = L_{g2}(y_1, y_2)$

$$\therefore g(y_1, y_2) = 2L_g(y_1, y_2) + \alpha. \quad (4)$$

Definition 5. The difference $c(y_1, y_2)$ between the two image words y_1 and y_2 is the sum of the difference distance and the difference adjustment parameter. If the difference adjustment parameter of the image word similarity is β , then

$$c(y_1, y_2) = L_{c1}(y_1, y_2) + L_{c2}(y_1, y_2) + \beta, \quad (5)$$

$$\therefore L_{c1}(y_1, y_2) = L_{c2}(y_1, y_2), \quad (6)$$

and set $L_c(y_1, y_2) = L_{c1}(y_1, y_2) = L_{c2}(y_1, y_2)$

$$\therefore c(y_1, y_2) = 2L_c(y_1, y_2) + \beta. \quad (7)$$

Therefore,

$$\text{sim}(y_1, y_2) = \frac{2L_g(y_1, y_2) + \alpha}{2L_g(y_1, y_2) + 2L_c(y_1, y_2) + \alpha + \beta}. \quad (8)$$

The number of paths taken by each image word from the root node O to the position of the image word is 5, and each path has a different weight. Suppose that the weight of the path from the root node to the word position is $Q(r)$, $r \in [1, 5]$:

$$L_g(y_1, y_2) = \sum_{i=1}^k Q(r), \quad (9)$$

$$L_c(y_1, y_2) = \sum_{i=k+1}^{k+j} Q(r). \quad (10)$$

Then, suppose that n is the number of nodes in the next layer of the nearest public parent node of the two image words, m is the number of intervals in the next layer of the nearest public parent node of the two image words, and $Q(k)$ represents the path weight of the nearest public parent node K :

$$\beta = \frac{m}{n} Q(k). \quad (11)$$

Finally, the similarity between y_1 and y_2 is given as

$$\text{sim}(y_1, y_2) = \frac{2\sum_{r=1}^k Q(r) + \alpha}{2\sum_{r=1}^{k+j} Q(r) + (m/n)Q(k) + \alpha}. \quad (12)$$

In Tongyici Cilin, when the first five layers (the first 7 bits in the code) of the two image words' tree structures are the same, the similarity is determined by the 8th bit's encoding. The 8th bit's code is "=", "#", or "@"—they represent similarities of the two image words of 1, 0.5, and 0, respectively. If an image word has multiple codes in Tongyici Cilin, the maximum value of the two image's word similarities is taken as the final similarity value. If the image word y_1 has w codes, and the image word y_2 has v codes, then

$$\text{sim}(y_1, y_2) = \max_{i=1,2,\dots,w; j=1,2,\dots,v} \{\text{sim}(y_1(i), y_2(j))\}, \quad (13)$$

where $\text{sim}(y_1(i), y_2(j))$ represents the similarity value between the i -th code of the image word y_1 and the j -th code of the image word y_2 . As shown in Figure 4, taking the two image words of "gorgeous" and "handsome" as examples, the code of "gorgeous" is "Eb32A01=", and the codes of "handsome" are "Ee35A01=" and "Bg05A02=" in the word code proposed for Tongyici Cilin. The code "Bg05A02=" is excluded by

FIGURE 4: The tree structure of “gorgeous” and “handsome” in the Tongyici Cilin semantic dictionary.

TABLE 1: Similarity model evaluation standard data (from RG).

Word 1	Word 2	RG	Word 1	Word 2	RG
Graveyard	Mental hospital	0.1050	Graveyard	Cemetery	0.9700
Boy	Rooster	0.1100	Sedan	Car	0.9800
Laughing	Lad	0.2200	Gem	Treasure	0.9600
Seaside	Sailing	0.3050	Travel	Travel far	0.9600
Bird	Forest	0.3100	Boy	Lad	0.9400
Stove	Instrument	0.3425	Coastal	Seaside	0.9250
Crane	Cock	0.3525	Magician	Wizard	0.8750
Hills	Forest	0.3700	Noon	Midday	0.8550
Glass	Jewelry	0.4450	Bird	Cock	0.7625
Magician	Saints	0.4550	Bird	Crane	0.7425
Hills	Slope	0.8225	Tool	Instrument	0.7375
Serf	Slave	0.8650	Crane	Instrument	0.4200
Signature	Sign	0.8975	Lad	Fraternal	0.4150
Plantation	Forest	0.9125	Travel	Sedan	0.2900
Rooster	Cock	0.9200	Monk	Saints	0.2750
Pillow	Weeping willow	0.9600	Plantation	Graveyard	0.2100

considering the maximum similarity as the final similarity, and the codes of “Eb32A01=” and “Ee35A01=” are the same in the first layer. Thus, the nearest common parent node of the two image words “gorgeous” and “handsome” in the first layer—that is, $k=1$. Here, “gorgeous” and “handsome” have six nodes named Ea, Eb, Ec, Ed, Ee, and Ef in the $k+1$ layer, which means that $n=6$. The number of intervals between the Eb and Ee of the two image words “gorgeous” and “handsome” in the $k+1$ layer is 3, which indicates that $m=3$.

2.2.3. Parameter Determination of the Image Word Similarity Calculation Model. According to Equation (12), to determine the size of similarity $\text{sim}(y_1, y_2)$, the values of $Q(r)$ and α must first be determined. Therefore, in combination with the characteristics of the Tongyici Cilin tree structure, the following principles should be followed when determining the parameters of the similarity model. First,

as r increases, $Q(r)$ increases. Second, as r increases, the range in which $Q(r)$ increases is small, and the magnitude does not exceed the size of $Q(r)$ itself. Third, the common adjustment parameter α is not greater than 1. Fourth, perform an evaluation based on internationally accepted similarity evaluation data. Finally, the highly correlated, moderately correlated, and poorly correlated words should be relatively evenly distributed.

The data set published by Rubenstein and Goodenough (RG) [41] is currently the main global evaluation standard for similarity algorithms. It can be seen from RG that the numbers of terms with k values from 0 to 5 are 8, 17, 20, 9, 2, and 9. According to the principle that the number of words with different k values should be relatively evenly distributed, in RG, 6, 6, 6, 6, 2, and 6 words were selected from 0 to 5 according to their k values, as shown in Table 1. The words and RG values will be used as the basis for determining the

parameters of the word similarity calculation model in this paper.

The primary criterion for parameters determination of the similarity model is the Pearson correlation coefficient between the standard data and evaluated data. The larger the Pearson correlation coefficient is, the better the parameters of the similarity model will be. Through continuous testing, the Pearson correlation coefficient was determined to be 0.9371, and the values of $Q(r)$ and α are shown in Table 2.

The accuracy of the word similarity calculation model proposed in this study was found to be higher than that of the existing calculation models by comparison. As shown in Table 3, the Pearson correlation coefficient values are larger than the calculation results using the formulas in the existing literature.

2.3. Determine the Product Form Styles of the Target Images. Product Kansei image design is to determine the mapping relationship between design elements and user emotions. In the product form innovation design, design elements are the appearance form of the product, which can be represented by product research samples. A research sample represents the form of a product, that means a research sample expresses the design elements of a product and at the same time expresses a style of the product. User emotions are the inner emotion that users expect from product form. In this research, user emotions are expressed by target image words determined by similarity calculation and cluster analysis.

The purpose of the product image form design survey is to construct the mapping relationship between the target image words and the research samples to determine the product form styles of the target images. In the past, this type of survey was completed by a paper questionnaire and Likert Scale. This process required not only designing the questionnaire, issuing the questionnaire, filling in the questionnaire, and returning the questionnaire, but also data entry and statistical analysis of the questionnaire data. This traditional method thus involves a cumbersome process and an enormous amount of data. Therefore, modern network information technology was applied to develop a network-based product image modeling design investigation system in this study.

2.3.1. User Types of the Product Image Design Investigation System. The proposed system is divided into super administrators, administrators, and subjects according to user types. The super administrators can maintain basic information, and the administrators can create new surveys, publish surveys, view surveys, and close surveys. The administrators can also analyze and export the data, such as the similarity data, cluster analysis data, and survey questionnaire results. In addition, the administrators can input basic questionnaire information, set the score range, and upload research samples into the product image design survey system, as shown in Figure 5.

The subjects can evaluate the image words corresponding to the research samples in this system. The results of the questionnaire represent the Kansei image cognition of the subjects for product samples. To analyze the image perceptions of

TABLE 2: Parameters of the image word similarity calculation model.

Parameters	$Q(1)$	$Q(2)$	$Q(3)$	$Q(4)$	$Q(5)$	α
Value	1	1.05	1.1	1.15	1.2	0.8

TABLE 3: Comparison of the Pearson correlation coefficients calculated by different methods.

No.	Methods	Pearson correlation coefficient
1	Formula of Liu et al. [42]	0.8086
2	Formula of Hao et al. [43]	0.8252
3	Formula of Tian and Zhao [33]	0.5204
4	Formula of Chen et al. [41]	0.8560
5	Formula of this paper	0.9371

different users, the subjects need to provide information, such as region of residence (province, city, and district), age, gender, educational background, annual income, and user's type, when registering in this survey system.

2.3.2. Function of the Product Image Design Investigation System. Using the "Spring + Mybatis" development framework and the MySQL database, the product image design investigation system was developed with Tomcat Web Servers and the SPSS 22 "Statistical Products and Service Solutions" software based on the JAVA language. This system can provide a log service, search service, persistence service, cache service, and authorization service, along with file storage. The core function includes three modules: a similarity calculation, cluster analysis, and a product image design survey.

To avoid multiple inputs and outputs of data and realize the seamless connection of similarity calculations, cluster analysis, and product image design investigations, the calculation data of image word similarities can be directly used for cluster analysis, and the cluster analysis results can be directly used for product image design investigations. Therefore, combining the three functional modules of similarity calculations, cluster analysis, and product image design investigations not only conforms to the product image design process but also improves the efficiency of product image design.

The similarity calculation includes two steps, the code determination and the operation, which can be seen in Figure 6. First, the code is determined by matching the image word with the Tongyici Cilin database. Second, the operation is based on the similarity calculation model (including common distance, difference distance, common adjustment parameter, and difference adjustment parameter) to determine the similarity value.

This survey system also includes a cluster analysis function based on the K -means cluster analysis algorithm. The cluster analysis loop operation ends when one of the following conditions is met: the number of iterations is reached, the N image words reach convergence, the K centroids reach

FIGURE 5: Administrator interface of the product image design investigation system based on the Tongyici Cilin.

FIGURE 6: Calculation process of image words similarity based on the Tongyici Cilin semantic dictionary.

convergence, or the sum of variance is less than the threshold value. This survey system can perform cluster analysis based on image word similarity data and can determine the target image words according to the cluster analysis results. The product image design survey is based on the semantic difference method and is used to analyze the users' image cognition of the research samples. The cognition level is reflected by the image word evaluation scores.

3. Case Study

According to Figure 1, sedan image design for middle-aged, middle-income men was carried out to further verify the proposed product image design investigation process. Then, the effectiveness of the image word similarity calculation model and the product image design survey system was tested.

TABLE 4: Initially determined sedan image words.

Handsome	Incomparable	Powerful	Lightsome	Excellent	Solid
Robust	Fluent	Athletic	Smooth	Splendid	Consecutive
Arrogant	Gliding	Sharp	Dependable	Beautiful	Steady
Mature	Tasteful	Traditional	Old fashioned	Wild	Full
Soft	Economic	Implicit	Exquisite	Trenchant	Personality
Pure	Capable	Gorgeous	Vitality	Security	Fashionable
Dynamic	Rough	Flexible	Classical	Lovely	Graceful
Reposeful	Solemn	Rational	Untrammelled	Popular	Representative
Laggard	Slim	Streamline	Elegant	Mellow	Affiliative
Inerratic	Gentle	Commercial	Stable	Moderate	Concordant

3.1. Determination of the Design Task. This article takes the image design of a sedan for middle-aged, middle-income men as an example. The target user group was determined to be middle-aged, middle-income men, and the target product was defined as a sedan through a demand analysis of the design target. The target user group was defined based on an annual income of over CNY 100,000, an age of 31–50 years, and male gender.

Therefore, the problem was characterized by combining the target people and the target product. From an aesthetic point of view, the target people have a relatively distinguished aesthetic taste and a relatively stable perception of product form. In addition, they cannot pursue very innovative and avant-garde looks. From the perspective of the economic consumption level, the target group belongs to the middle class. Therefore, the target group mainly considers middle-level products and would not pursue low-level products. From the perspective of the design type, this example was designed for styling imagery of a sedan. Thus, the sedan's overall form style was focused on while ignoring product details and branding. In summary, through demand analysis and problem characterization, the design task was determined as follows:

- (1) Men were identified as the target group of people
- (2) The age distribution range of the target group was 31–50 years old
- (3) The aesthetic perception of the target group was relatively stable
- (4) The economic level of the target group was relatively high
- (5) A sedan was defined as the target product
- (6) The focus was on middle level products
- (7) “Sedan” refers to a small car that differs from a truck, pickup, SUV, bus, and minibus
- (8) The focus was on the overall style of the target product
- (9) Image form design was implemented for the target products

TABLE 5: Image word collection for a sedan.

Handsome	Gorgeous	Personality	Steady	Fashionable
Powerful	Splendid	Arrogant	Implicit	Exquisite
Dynamic	Graceful	Solemn	Rational	Mature
Elegant	Tasteful	Concordant	Inerratic	Athletic
Excellent	Trenchant	Capable	Classical	Commercial

3.2. Collection of Image Words and Product Samples

3.2.1. Image Words. To determine the image words that can express the sedan form, the product style preferences of middle-aged, middle-income men were searched using the network platform. Sixty image words that express the shape of a sedan were preliminarily determined, as shown in Table 4.

Under the product image design requirements, design experts conducted comprehensive comparative analyses of the collected sedan image words and completed screening to reduce the workload of the statistical analysis. Several principles were followed. First, the image words with obvious derogation and ambiguity were deleted. Second, the image words that did not conform to the sedan design were deleted. Third, we added other image words that can express the form of a sedan. Then, the remaining 25 image words were used as the image word set for middle-aged, middle-income men's sedan design, as shown in Table 5.

3.2.2. Product Samples. According to the determined design task, sedan pictures were collected on the “Qi Che Zhi Jia” network platform. To collect as many sedan-style pictures as possible, the overall outlines of the sedans were emphasized, and factors such as details, prices, and brands were ignored during the search process. Thirty pictures of sedan samples were initially selected as a collection of product samples designed for middle-aged, middle-income men.

3.3. Determination of Target Images

3.3.1. Similarity Calculations. Two different methods were used to determine the similarities of the image words. One was the traditional similarity determination method (referred to as method 1); the other one was the similarity calculation based on Tongyici Cilin, as proposed in this article (referred

TABLE 6: Relationship between similarity values and image word similarities.

Image word similarity	Same	Similar	Relatively similar	Relatively dissimilar	Very dissimilar	Different
Similarity value	1	0.8	0.6	0.4	0.2	0

to as method 2). Then, method 2 was further verified through comparison between the two.

(1) *Method 1: Using the Traditional Method to Determine Similarities.* First, the similarity questionnaire asked the subjects to fill in a 25 * 25 similarity matrix for the 25 image words in Table 5. The relationship between the similarity value and the image word similarity is shown in Table 6. Second, the questionnaire was produced, distributed, and withdrawn. Male users 31–50 years old with annual incomes greater than or equal to CNY 100,000 were invited to rate the design task. Eighteen questionnaires on sedan image word similarities were distributed among the middle-aged, middle-income men, and 15 were recovered. Third, the data of the 15 questionnaires were processed and statistically analyzed, and then the average was weighted. Finally, 625 sets of car image word similarity data from the traditional similarity survey data were obtained. In this process, 9375 valid questionnaire data will be generated. Taking into user fatigue factors, this method is not only cumbersome, but also the accuracy is questionable.

(2) *Method 2: Using the Similarity Calculation Model to Determine Similarities.* The operation process for the similarity calculation is relatively simple using the proposed method. By simply inputting or pasting the image words into the initial image word column of the “Product Image Modeling Design Investigation System” and clicking the “Similarity Calculation” button, the similarity calculation results for the image words can be obtained, and the similarity data can be exported.

(3) *Validity Test.* To further analyze the effectiveness of method 2, 30 groups of words were randomly selected as standard words for validity verification from 625 groups of sedan image words in the traditional similarity survey data, and the similarity values determined by the traditional methods were used as the standard similarity values. Then, the similarity value of the above 30 groups of words calculated in the survey system developed in this paper was used as the evaluated similarity value. The Pearson correlation coefficient between the standard similarity value and the evaluated similarity value was calculated, as shown in Table 7.

As shown in Table 7, the Pearson correlation coefficient value was 0.9491, showing that the image word similarity calculation model constructed by Tongyici Cilin is effective.

(4) *Comparative Analysis.* Based on a comparison of the above two methods, using the “Product Image Modeling Design Investigation System” developed in this paper to calculate the similarity of image words has the following advantages.

TABLE 7: Calculation of the Pearson correlation coefficient using the two methods.

Image word 1	Image word 2	Similarity value	
		Method 1	Method 2
Mature	Tasteful	0.2667	0.2356
Dynamic	Tasteful	0.2333	0.2292
Inerratic	Capable	0.4	0.392
Dynamic	Solemn	0.2333	0.2308
Dynamic	Exquisite	0.2333	0.2308
Capable	Exquisite	0.4	0.3976
Mature	Classical	0.2333	0.2356
Inerratic	Classical	0.4	0.41
Powerful	Powerful	1	1
Tasteful	Athletic	0.2333	0.2308
Exquisite	Athletic	0.2333	0.2324
Dynamic	Gorgeous	0.3667	0.2308
Handsome	Rational	0.2333	0.2356
Inerratic	Rational	0.4333	0.4126
Classical	Excellent	0.2333	0.2356
Rational	Excellent	0.2333	0.2356
Excellent	Excellent	1	1
Inerratic	Steady	0.3667	0.392
Excellent	Steady	0.4	0.4092
Dynamic	Elegant	0.2333	0.2308
Implicit	Elegant	0.4	0.4
Mature	Personality	0.2333	0.2356
Solemn	Fashionable	0.2333	0.2356
Commercial	Graceful	0.2333	0.2356
Excellent	Graceful	0.4	0.4033
Elegant	Graceful	0.6	0.6002
Inerratic	Concordant	0.4	0.3976
Mature	Powerful	0.4	0.2356
Mature	Athletic	0.2	0.4062
Mature	Gorgeous	0.2333	0.3976
Pearson correlation coefficient		0.9491	

One is the proposed method’s objectivity, which can avoid design errors caused by different subjects’ preferences and subjective cognitive tendencies. Method 2 was derived from the encoding of image words in the Tongyici Cilin database. The encoding of the image words is determined in the database, which is more objective than the manual scoring of method 1. Therefore, the similarity calculation results of method 2 are unique, which provides strong technical support for intelligent design.

TABLE 8: Part similarity data of image words.

Similarity	Handsome	Gorgeous	Personality	Steady	Fashionable	Powerful	Splendid	Arrogant	Implicit	Exquisite	Dynamic
Handsome	1.0	0.3976	0.2356	0.5941	0.2356	0.2356	0.2356	0.5979	0.5646	0.3976	0.2308
Gorgeous	0.3976	1.0	0.2356	0.3976	0.2356	0.2356	0.2356	0.4033	0.3976	0.6002	0.2308
Personality	0.2356	0.2356	1.0	0.2356	0.4050	0.5624	0.7423	0.4050	0.2356	0.2356	0.2292
Steady	0.5941	0.3976	0.2356	1.0	0.2356	0.2356	0.2356	0.5904	0.5714	0.3976	0.2308
Fashionable	0.2356	0.2356	0.4050	0.2356	1.0	0.4050	0.4050	0.5890	0.2356	0.2356	0.2292
Powerful	0.2356	0.2356	0.5624	0.2356	0.4050	1.0	0.5624	0.4050	0.2356	0.2356	0.2292
Splendid	0.2356	0.2356	0.7423	0.2356	0.4050	0.5624	1.0	0.4050	0.2356	0.2356	0.2292
Arrogant	0.5979	0.4033	0.4050	0.5904	0.5890	0.4050	0.4050	1.0	0.5613	0.4033	0.2308
Implicit	0.5646	0.3976	0.2356	0.5714	0.2356	0.2356	0.2356	0.5613	1.0	0.3976	0.2356
Exquisite	0.3976	0.6002	0.2356	0.3976	0.2356	0.2356	0.2356	0.4033	0.3976	1.0	0.2308
Dynamic	0.2308	0.2308	0.2292	0.2308	0.2292	0.2292	0.2292	0.2308	0.2356	0.2308	1.0

The second benefit is the proposed method's high efficiency. Method 2 is directly calculated by an online computer network that requires a short runtime. However, method 1 requires information from a certain amount of similarity questionnaires. In addition, method 1 involves the design, distribution, filling, withdrawing, data sorting, and calculations of the questionnaire. For method 2, the survey system based on the network platform provides the possibility for the collaborative participation of designers and subjects from different regions.

3.3.2. Cluster Analysis. As shown in Figure 1, a cluster analysis of similarity data is needed to classify the image words, so as to determine the target image words. Therefore, the word similarity data for clustering analysis was determined by the Tongyici Cilin similarity calculation model, as shown in Table 8, which is part similarity data of image words from method 2.

In the process of clustering N image words into K categories, the K -means clustering analysis first randomly selects K image words from N image words as the initial centroids. Then, the distances from the remaining image words to the initial centroids are calculated, and the remaining image words are classified into the category of the closest distance. The N image words were divided into K categories in this cycle. In the K -means cluster analysis, all the image words must be vectorized.

After N image words are divided into K categories, the image word in each category closest to the centroid position is selected as the representative image word in that category; either, one word in each category can be manually selected as the representative image word of that category. The target images of the product form design were composed of K representative image words. In this case study, the image words were set into four categories. As shown in Table 9, the four target image words of "handsome," "graceful," "powerful," and "tasteful" were ultimately selected for the target images of the sedan design for middle-aged, middle-income men, based on the cluster analysis results.

3.4. Determination of Research Samples. As shown in Figure 1, the research sample was determined by a designer's compara-

TABLE 9: Image word clustering analysis results.

Category 1	Category 2	Category 3	Category 4
Handsome	Gorgeous	Personality	Dynamic
Steady	Exquisite	Fashionable	Tasteful
Arrogant	Graceful	Powerful	Athletic
Implicit	Elegant	Splendid	
Solemn		Rational	
Mature		Inerratic	
Concordant		Classical	
Excellent		Commercial	
Trenchant			
Capable			

tive analysis based on a collection of product samples. In this example, the designer conducted the comparative analysis of 30 sedan samples to determine the research samples. To eliminate the errors caused by different viewing angles and colors in the evaluation of a sedan image, white sedans and sedans at a 45-degree viewing angle were selected through comparative analysis. At the same time, we sought to ensure that only moderately sized cars were selected, so the size of cars that were too big or too small was deleted. The final research samples used in the image design for middle-aged, middle-income men's sedans are shown in Table 10.

3.5. Determination of the Product Form Design Style. In order to clarify the product form style corresponding to each target image, this case study determined the mapping relationship between the target images and the product samples. This process was completed on the product image form design investigation platform developed by this research. Middle-aged, middle-income men were invited to evaluate the images of 24 research samples using four target images. We have adopted the semantic difference method for product image evaluation and set up a five-level semantic scale. For the four target image words of "handsome," "graceful," "powerful," and "tasteful," each target image was scored

TABLE 10: Research samples of sedans image form design.

No. 1		No. 2		No. 3		No. 4		No. 5		No. 6		No. 7		No. 8
No. 9		No. 10		No. 11		No. 12		No. 13		No. 14		No. 15		No. 16
No. 17		No. 18		No. 19		No. 20		No. 21		No. 22		No. 23		No. 24

according to the five levels of “-2,” “-1,” “0,” “1,” and “2.” Taking “handsome” as an example, “-2” means “not at all handsome,” “-1” means “relatively not handsome,” “0” means “between relatively not handsome and relatively handsome,” “1” means “relatively handsome,” and “2” means “very handsome.”

In order to ensure the accuracy of the questionnaire data, in case study, the subjects were required to browse all research samples first to generate an overall impression of each research sample, and then rating. In addition, we will clearly inform subjects that this questionnaire is to determine the image evaluation of the research samples from the perspective of the overall style of the product form, so as to further enable the subjects to understand the purpose and significance of the investigation, to improve the accuracy of the questionnaire.

4. Results

As shown in Table 11, the survey data was derived by implementing the product image design survey. As can be seen from Table 11, survey users come from 14 provinces in China, including Jiangsu, Shanghai, Gansu, Beijing, Guizhou, Hainan, Sichuan, Hebei, Ningxia, Zhejiang, Hunan, Liaoning, Fujian, and Hubei. In terms of age range, 16 users were aged 31–40, accounting for 53.28%, and 8 users were aged 41–50, accounting for 26.64%. From the perspective of educational background, there were 13, 13, and 4 users with bachelor's degrees, master's degrees, and doctorates (or above), accounting for 43.29%, 43.29%, and 13.32%, respectively. In terms of annual income levels, there were 11, 8, and 6 people with annual income of CNY 100,000-150,000, CNY 150,000-200,000, and CNY 200,000 or more, respectively, accounting for 36.63%, 26.64%, and 19.98%, respectively.

The image evaluation data that did not meet the requirements was deleted. The final number of valid questionnaires was 24. By normalizing the 24 questionnaires, the car image evaluation data was obtained. Then, research samples with higher image evaluation values were obtained to represent the form styles corresponding to the Kansei images, as shown in Table 12. It can be seen that the scores of four research samples were high, meaning that they basically achieved the form style of the corresponding Kansei image words.

5. Discussion

The main scientific values and significances of this study are as follows. First, the introduction of Chinese semantic dictionaries into Kansei engineering provides new technologies and methods for the research of Kansei engineering. Second, the accuracy of the word similarity calculation model proposed in this study is higher than that of the word similarity calculation models already exist, which has made a certain contribution to the semantic word similarity calculation and natural language processing. Third, in-depth study of the coding rules of the Tongyici Cilin semantic dictionary, starting from the coding rules of the Tongyici Cilin and the essence of the intrinsic semantic relationship, discussing the calculation method of image word similarity based on

the Tongyici Cilin semantic dictionary, providing a new method for calculating the word similarity. Fourth, starting from the theory of natural language processing, a new method for determining design goals in product form innovation design is proposed, which is more objective, efficient, and scientific than traditional methods. Fifth, the research results provide new value for product design, Kansei engineering, emotional design, natural language processing in product form innovation design, target images determination, user emotion mining, and word similarity calculation.

In addition, this paper presents the feasibility of this research from two perspectives. On the one hand, it is verified from the image word similarity calculation model proposed by this article and the international word similarity calculation standard data. When determining the target images, by comparing the image word similarity value obtained by the method in this article and the image word similarity value obtained by the international standard data, the Pearson correlation coefficient value of the two methods was 0.9491. This shows that the image word similarity calculation model proposed in this paper can accurately determine target images. On the other hand, the case study verified the effectiveness and explained the internal mechanism of the proposed method. It can be seen at the theoretical and factual levels that the methods for determining design goals in product form innovation design proposed in this paper are feasible.

Finally, we discuss the innovation of the image word similarity calculation model from the four aspects of scientificity, accuracy, objectivity, and efficiency. The first is the scientificity of the image word similarity calculation model. According to the principle of word similarities, the method proposed in this paper to determine the similarities among image word using common distance, difference distance, common adjustment parameter, and difference adjustment parameter is scientific. Because the common distance and difference distance of the image vocabulary similarity calculation model are determined by the coding rules of Tongyici Cilin. Moreover, the variation ranges of the common adjustment parameter and the difference adjustment parameter are strictly limited. For example, the variation range of $Q(r)$ does not exceed the value of $Q(r)$ itself, and the common adjustment parameter α is not greater than 1. In the verification of the similarity calculation model, the numbers of words with high, medium, and low correlations in the standard data are relatively uniform. The second is the accuracy of the image word similarity calculation model. The image word similarity data were obtained from the database of Tongyici Cilin. Therefore, the image word similarity value determined by this research is uniquely determined. The third is the objectivity of the image word similarity calculation model. The value of the image word similarity was not determined by the user's subjective evaluation, which avoided errors caused by the user's academic qualifications, experience, cognition, and other factors. Finally, in terms of efficiency, the method proposed in this paper was able to determine the target images in less than 1 min, whereas the current go-to method requires at least 4 h to determine the target images. Therefore, the image word similarity calculation model proposed in this paper can not only improve the accuracy and objectivity of determining the target images but can also

TABLE 11: Participant distribution.

Total number of users participating in the survey: 30															
Provinces/Municipalities		Jiangsu	Shanghai	Gansu	Beijing	Guizhou	Hainan	Sichuan	Hebei	Ningxia	Zhejiang	Hunan	Liaoning	Fujian	Hubei
Population	2	1	3	3	3	5	1	1	3	4	1	1	2	2	1
Percentage	6.66%	3.33%	9.99%	9.99%	9.99%	16.65%	3.33%	3.33%	9.99%	13.32%	3.33%	3.33%	6.66%	6.66%	3.33%
Age	Under the age of 18			18 to 30		31 to 40		41 to 50		51 to 60		More than 60			
Population	0			5		16		8		0		1			
Percentage	0.00%			16.65%		53.28%		26.64%		0.00%		3.33%			
Gender	Male			Female			Unknown								
Population	28			2			0								
Percentage	93.24%			6.66%			0.00%								
Education background	Junior college and below			Bachelor		Masters		Doctorate and above							
Population	0			13		13		4							
Percentage	0.00%			43.29%		43.29%		13.32%							
Annual income (CNY)	50,000 the following			50,000–100,000		100,000–150,000		150,000–200,000		More than 2,000,000					
Population	5			0		11		8		6					
Percentage	16.65%			0.00%		36.63%		26.64%		19.98%					

TABLE 12: Sedan styles corresponding to the four target images.

Image words	Handsome	Graceful
No.	No. 2	No. 9
Research samples
Image evaluation	1	0.9091
Image words	Powerful	Tasteful
No.	No. 17	No. 16
Research samples
Image evaluation	1.0417	0.9545

improve the efficiency of determining the target images and further improve the scientificity of product’s Kansei image design.

However, there are still some limitations in this research. For example, the number of words in Tongyici Cilin is not endless, so there may be a few image words that do not exist in this database. Moreover, this study adopted a mainstream Chinese synonym dictionary, allowing the results to better reflect the Chinese people’s preferences in product image form, but this may lead to certain limitations in other countries. Finally, the number of subjects is limited, so the experimental results may have certain limitations.

A future research direction is to explore product Kansei image design based on a mixture of different semantic dictionaries. Another future research direction would be to use deep learning algorithms to build an intelligent product image design system based on Tongyici Cilin.

6. Conclusion

In this study, we used the methods of Kansei engineering, cluster analysis, and Likert scale to realize product emotional design. We used the word similarity calculation based on the Tongyici Cilin semantic dictionary to realize the target image mining of the product form innovation design, and the main conclusions are as follows.

- (1) The complete process of product image design based on Tongyici Cilin semantic dictionary was proposed and verified through examples. The process of product image design based on Tongyici Cilin semantic dictionary included five stages: determining the design tasks, collecting the image word and product samples, determining the target images, determining the research samples, and establishing the questionnaire

- (2) An image word similarity calculation model based on Tongyici Cilin semantic dictionary was creatively constructed to make the image word similarity data more objective and improve the efficiency of determining the target images
- (3) The parameters of the similarity calculation model were determined via international standard verification. We verified that the similarity calculation method proposed in this paper is better than the methods already exist
- (4) A web-based “Product Image Modeling Design Investigation System” was constructed. In this survey system, the three modules of similarity calculations, cluster analysis, and product image design surveys were combined to achieve a seamless data connection. In addition, the product image modeling design investigation system provides conditions for cross-regional collaborative design

In summary, this study introduces word similarity calculation into the field of Kansei engineering and improves the accuracy, objectivity, and efficiency of target image mining in product form image design.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] J. N. Su, Q. W. Zhang, J. H. Wu, and Y. Liu, "Evolutionary design of product multi-image styling," *Computer Integrated Manufacturing Systems*, vol. 20, pp. 2675–2682, 2014.
- [2] T. Wang and M. Zhou, "A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction," *International Journal of Industrial Ergonomics*, vol. 76, 2020.
- [3] Z. H. Zhou, *Analysis on Philosophical Problems of Cognitive Thinking*, Shanxi University, Shanxi, China, 2016.
- [4] M. Nagamachi, "Kansei engineering: a new ergonomic consumer-oriented technology for product development," *International Journal of Industrial Ergonomics*, vol. 15, pp. 3–11, 1995.
- [5] Q. W. Zhang, *Research on the Evolutionary Design of Product Multi-Object Image Modeling*, Lanzhou University of Technology, 2014.
- [6] Z. Q. Jian, *Industrial Design Methodology*, Beijing Institute of Technology Press, Beijing, China, 2011.
- [7] G. D. Chen, S. Y. Chen, J. Wang, S. Q. Sun, and Y. H. Ni, "Multi-objective optimization method of composite imagery-oriented product form," *China Mechanical Engineering*, vol. 26, pp. 2763–2770, 2015.
- [8] J. Y. Kuo, C. H. Chen, J. R. Roberts, and D. Chang, "Evaluation of the user emotional experience on bicycle saddle designs via a multi-sensory approach," *International Journal of Industrial Ergonomics*, vol. 80, 2020.
- [9] F. Guo, Q. X. Qu, M. Nagamachi, and V. G. Duffy, "A proposal of the event-related potential method to effectively identify Kansei words for assessing product design features in Kansei engineering research," *International Journal of Industrial Ergonomics*, vol. 76, 2020.
- [10] W. F. Hu, J. H. Zhao, and D. H. Zhao, "Study on styling image of vehicle based on form feature lines," *China Mechanical Engineering*, vol. 20, pp. 496–500, 2009.
- [11] W. F. Hu and J. H. Zhao, "Automobile styling gene evolution driven by users' expectation image," *Journal of Mechanical Engineering*, vol. 47, pp. 176–181, 2011.
- [12] C. Jing and J. Zhao, "Optimization design method of automobile styling based on evolution strategy," *China Mechanical Engineering*, vol. 25, pp. 1517–1523, 2014.
- [13] S. J. Luo, Y. T. Fu, and Y. X. Zhou, "Perceptual matching of shape design style between wheel hub and car type," *International Journal of Industrial Ergonomics*, vol. 42, pp. 90–102, 2011.
- [14] H. C. Yadav, R. Jain, S. Shukla, S. Avikal, and P. Mishra, "Prioritization of aesthetic attributes of car profile," *International Journal of Industrial Ergonomics*, vol. 43, pp. 296–303, 2013.
- [15] L. Chen, R. F. Shu, and H. H. Zhou, "Research on mining method of perceptual needs of product form in commercialization of new technology," *China Mechanical Engineering*, vol. 21, pp. 2803–2808, 2010.
- [16] H. Zhou, L. Chen, and W. Hu, "On selection of texture image and surface craft under target form image," *China Mechanical Engineering*, vol. 23, pp. 2671–2675, 2012.
- [17] Y. E. Yeh, "Prediction of optimized color design for sports shoes using an artificial neural network and genetic algorithm," *Applied Sciences*, vol. 10, pp. 1560–1579, 2020.
- [18] Y. Wu, "Product form evolutionary design system construction based on neural network model and multi-objective optimization," *Journal of Intelligent Fuzzy Systems*, vol. 39, pp. 7977–7991, 2020.
- [19] Y. P. Yang, D. K. Chen, S. H. Yu, M. J. Yu, and B. Qi, "Pan-ethnic-group product form design based on shape grammar," *Computer Integrated Manufacturing Systems*, vol. 19, pp. 2107–2115, 2013.
- [20] M. Hartono, "The modified Kansei engineering-based application for sustainable service design," *International Journal of Industrial Ergonomics*, vol. 79, 2020.
- [21] C. N. Zabotto, S. Sergio Luisda, D. C. Amaral, H. CJM, and B. G. Benze, "Automatic digital mood boards to connect users and designers with Kansei engineering," *International Journal of Industrial Ergonomics*, vol. 74, 2019.
- [22] K. Qiu, J. Su, X. Zhang, and W. Yang, "Evaluation and balance of cognitive friction: evaluation of product target image form combining entropy and game theory," *Symmetry*, vol. 12, pp. 1398–1417, 2020.
- [23] L. Wu, H. Gao, K. C. Wang, and C. H. Yang, "A green-IKE inference system based on grey neural network model for humanized sustainable feeling assessment about products," *Mathematical Problems in Engineering*, vol. 2020, Article ID 6391463, 9 pages, 2020.
- [24] X. Zhang and M. Yang, "Color image knowledge model construction based on ontology," *Color Research and Application*, vol. 44, pp. 651–662, 2019.
- [25] L. Xue, X. Yi, and Y. Zhang, "Research on optimized product image design integrated decision system based on Kansei engineering," *Applied Sciences*, vol. 10, pp. 1198–1217, 2020.
- [26] J. Du, Y. Li, J. Ma, Y. Xiong, and W. Li, "Retrieval of semantic-based inspirational sources for emotional design," *Computational Intelligence and Neuroscience*, vol. 2018, Article ID 4685187, 17 pages, 2018.
- [27] C. Y. Liu and L. I. Tong, "Developing automatic form and design system using integrated grey relational analysis and affective engineering," *Applied Sciences*, vol. 8, pp. 91–113, 2018.
- [28] N. Jing, J. N. Su, and S. T. Zhang, "Product modeling design based on cognition reconstructed on traditional artifact," *Package Engineering*, vol. 37, pp. 90–94, 2016.
- [29] B. C. Zhang, W. M. Guo, Y. Q. Wang, S. C. Li, Y. Huang, and J. Xu, "Train's interior form design oriented visual image of passenger research," *Journal of Mechanical Engineering*, vol. 52, pp. 199–205, 2016.
- [30] G. Yao, C. Xue, H. Wang, and B. Yan, "Design method for coach styling design based on image cognition," *Journal of Southeast University*, vol. 46, pp. 1198–1203, 2016.
- [31] L. F. Xiao, *Synonym Discovery Based on the Searching Information*, University of Electronic Science and Technology, Chengdu, China, 2018.
- [32] X. X. Wu, B. L. Li, and T. Q. Zhang, "A KNN based forensic method of Android smartphone WeChat," *Journal Shandong University*, vol. 49, 2014.

- [33] J. L. Tian and W. Zhao, "Words similarity algorithm based on Tongyici Cilin semantic web adaptive learning system," *Journal of Jilin University*, vol. 28, pp. 602–608, 2010.
- [34] X. Zhu, Q. Xu, Y. Chen, H. Chen, and T. Wu, "A novel class-center vector model for text classification using dependencies and a semantic dictionary," *IEEE Access*, vol. 8, pp. 24990–25000, 2020.
- [35] Y. Liang, W. Zhang, and K. Yang, "Attention-based Chinese word embedding," in *Cloud computing and security*, X. Sun, Z. Pan, and E. Bertino, Eds., pp. 277–287, Springer International Publishing, Cham, 2018.
- [36] J. C. Li and S. Yin, "The demand for moving line in the commercial space environment," *Package Engineering*, vol. 36, pp. 122–126, 2015.
- [37] K. Yang, W. Q. Li, Y. Li, and Y. Xiong, "Product innovative design service cognitive composition model based on SOA," *Computer Integrated Manufacturing Systems*, vol. 20, pp. 2329–2339, 2014.
- [38] J. J. Mei, *Tongyici Cilin*, Shanghai Dictionary Publishing House, Shanghai, China, 1983.
- [39] Q. Peng, X. Zhu, Y. Chen, L. Sun, and F. Li, "IC-based approach for calculating word semantic similarity in CiLin," *Application Research of Computers*, vol. 35, pp. 400–404, 2018.
- [40] W. X. Che, Y. Feng, L. Qin, and T. Liu, *N-ltp: A Open-Source Nneural Chinese Language Technology Platform with Pre-trained Models*, Computer Science, 2020.
- [41] H. C. Chen, F. Li, X. H. Zhu, and R. C. Ma, "A path and depth-based approach to word semantic similarity calculation in cilin," *Journal of Chinese Information Processing*, vol. 30, pp. 80–88, 2016.
- [42] X. Liu, Y. Zhou, and R. Zheng, "Measuring semantic similarity in Wordnet," in *2007 international conference on machine learning and cybernetics*, pp. 3431–3435, IEEE, Hong Kong, China, 2007.
- [43] D. Hao, W. Zuo, T. Peng, and F. He, "An approach for calculating semantic similarity between words using WordNet," in *2011 second international conference on digital manufacturing & automation*, pp. 177–180, Zhangjiajie, China, 2011.