

## Research Article

# Big Data-Driven Product Innovation Design Modeling and System Construction Method

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In order to improve the image quality of innovative design of manufacturing products, reduce the dependence on experts, increase the amount of research data, and accurately sort and select the best alternatives, this paper proposes the KENPI method, which integrates perceptual engineering and neural style transfer, normalizes the content map through nm model, realizes style transfer, and generates new product images. Use ORDD perceptual engineering to collect a large number of perceptual word data, establish product semantic space, use TF-EPA to obtain perceptual words, and use word clustering combined with degree adverbs to evaluate the sensibility of products. Under the KE-GRA-TOPSIS method, considering user preferences, accurately sort and select the product design alternatives with multiple criteria, and establish the auxiliary system of product innovative design. The experimental results show that the style transfer effect of nm model is better, the style intensity of the product is enhanced, and the average texture evaluation of sample 3 is increased by 0.30 points. The average absolute value of DOD phrase in BP neural network is 0.0765, which is lower than the MLR method, and the performance of the former is better than the latter. The relative closeness of A6 scheme under KE-GRA-TOPSIS method is 0.57, which is 0.02 higher than the KT method, indicating that the KE-GRA-TOPSIS method is better than the KT method. The research improves the way of obtaining user demand data, enhances the strength of and product style, and improves the competitiveness of products.

## 1. Introduction

Equipment manufacturing industry is the foundation of industries and plays an important supporting role in the development of the country and society. Its industry development level is an important standard to measure national and regional competitiveness. The prosperity and development of equipment manufacturing enterprises in major provinces of equipment manufacturing industry is of great significance to the country. Bai Zhu's innovation ability can effectively protect the core competitiveness of enterprises. Equipment manufacturing industry is a technology intensive industry. Based on independent innovation, mastering core technology is the lifeblood of enterprise development. Therefore, it is particularly important to

improve the independent innovation ability of equipment manufacturing enterprises in Liaoning Province.

China's equipment manufacturing industry mainly lacks independent intellectual property rights. Under the current development situation, if we are not able to carry out independent innovation, we will always be suppressed by western advanced countries and always rely on low prices to support the development of the industry. In the long run, it will lead to the loss of the development capacity of the entire equipment manufacturing industry. Driven by the globalization of the world economy, the competition between them has changed from price and quality competition to comprehensive ability competition. Therefore, China's equipment manufacturing industry must have independent intellectual property rights and carry out independent

innovation. Cultivating talents is an important way to improve the independent innovation ability of industry university research cooperation, and has important practical significance. Talent is a key factor in an industry. With the development of economic globalization, the development of talents gradually tends to the direction of internationalization. Under the background of fierce scientific and technological competition, the equipment manufacturing industry increasingly needs high-level talents and scientific and technological personnel as the support for development. Only the leading talents can enable enterprises to gain advantages and take the lead in the fierce market competition.

The development of manufacturing industry occupies a very important position in the national economic development, which can largely reflect a country's comprehensive national strength [1]. The independent innovation ability of domestic manufacturing industry needs to be improved, and the utilization rate of resources is not high. In 2015, the state strongly advocated to make use of emerging information technologies such as big data and the Internet, and carry out innovative design in combination with information technology in industrial design, so as to improve the innovation ability of industrial design [2]. The core of industrial design is product design, which reflects the consumer demand of users through products, brings benefits to enterprises, and supports the development of enterprises through product sales. The design concept of products has changed from "user-centered" to computer-aided product design [3]. In the user-oriented product design, we pay more attention to the feelings of users, and perceptual engineering is one of the design methods. However, the acquisition of user requirements is the difficulty of product design, and there is no intuitive visual display. In the innovative design, the dependence on the designer is very large, the subjectivity is strong, the demand of users cannot be responded quickly, and the success rate of products is low. Big data can solve the problems existing in manufacturing product design to a certain extent and has high information utilization value in user demand capture, product feedback, and so on. This paper will apply big data and perceptual engineering in product innovation design of manufacturing industry to solve the problems of poor picture quality and less research data in product innovation design.

This paper uses neural style transfer model and back propagation (BP) neural network mapping model to automatically recognize, extract, and reconstruct image features and combines it with perceptual engineering to form Kansei Engineering and Neural Style Transfer for Product Innovation (KENPI), so as to transfer the style of style map to product modeling. Through online review data-driven perceptual engineering analysis, online review, collection and acquisition of perceptual words, and product perceptual evaluation. Through personalized product design scheme decision-making including Kansei Engineering (KE), grey relational analysis (GRA), and techniques for order preference by similarity to ideal solution (TOPSIS), the alternatives are accurately sorted and selected.

The innovation of the method proposed in this paper is that it can improve the quality of pictures through the

KENPI method, realize the controllable operation of design content and reduce the dependence on experts. Reduce the initiative of perceptual engineering by driving data online, increase the amount of research data and solve the problem of poor effectiveness. The user's personality preference is taken into account through the KE-GRA-TOPSIS method, and the scheme that meets the preference of decision makers is selected after sorting the alternatives to realize the personalized decision-making of the scheme.

The article is divided into four parts. The second part is literature review, which introduces the technology applied by domestic and foreign scholars in manufacturing product design, as well as the application of design application fields related to big data, perceptual engineering and in-depth learning in design; the third part puts forward the KENPI method, perceptual engineering of online comment driven data, and the KE-GRA-TOPSIS method to solve the problems existing in product innovation design, enhance product innovation, and meet the needs of decision makers; the fourth part analyzes the results of the research method, illustrates the feasibility and effectiveness of the research method through examples, and proves that the KENPI method can improve the image quality, the perceptual engineering of online comment driven data can obtain and analyze the user demand data, the KE-GRA-TOPSIS method can accurately sort the alternatives, and the alternatives with the highest relative closeness can meet the preferences of decision makers.

## 2. Related Works

The product design of China's manufacturing industry is a short board in the manufacturing industry. The innovation of product design is insufficient, the image quality generated by relevant models is poor, and the user demand data is difficult to obtain. These are the problems that need to be solved in the product design of manufacturing industry. Jrgensen et al. deal with various model-based tasks in product and process integration, design, innovation, and operation through functional modeling, and transform modeling objectives into required system attributes [4]. Guo et al. proposed the design scheme of "demand industrial design innovation market demand" based on industrial intelligence and big data technology. It can promote the improvement of industrial design innovation ability, help industrial enterprises save costs in R&D and shorten R&D cycle [5]. Lei et al. designed an accelerator based on network on optical chip (ONOC) to further accelerate the matching between citizen supply and demand in the sharing economy [6]. Lin et al. reconstructed the business process of digital content companies based on customer experience big data and explained the design process of the new model. Based on the proposed model in the stage of product application design and customer service, it can be used as a reference for the transformation and innovation of digital content enterprises [7]. Yang et al. applied multiattribute decision-making to automobile manufacturing and service industry and trained it through BP neural network. The average accuracy of this method is 93.19% [8]. Page et al. evaluated the applicability of big data practice to designers to

understand the environment that allows designers to take advantage of this new platform, including the practice of open data and the system needed to manage it [9]. Jing et al. proposed the classification of current algorithms in the field of NST and compared different NST algorithms qualitatively and quantitatively [10]. Joung et al. proposed a method of IPA from online reviews of product design. By combining the influence of input characteristics from multiple optimal neural networks to estimate the importance value of product attributes with low variance, it has high performance [11].

Bertoni et al. discussed the role and challenges of integrating data-driven design (DDD) models in the process of product innovation, and aims to formalize it in the evaluation matrix to guide the further development of DDD [12]. Han et al. optimized BP neural network through the optimization characteristics of genetic algorithm and constructed a hybrid GA-BP model, so as to effectively evaluate and screen out scientific design schemes [13]. Zhang et al. established a back propagation (BP) neural network based on differential evolution (DE) algorithm, which will be applied to estimate the electrical properties of flexible Ag/poly (amic acid) (PAA) composite structures and develop flexible materials suitable for their different structures [14]. Turumugon et al. used perceptual engineering technology to transform users' feelings and emotions into design elements and designed appropriate websites of higher education institutions by determining the standard web page design for cultivating emotional participation [15]. Zhou et al. proposed a personalized recommendation model and algorithm based on perceptual engineering, traditional filtering algorithm, and clothing related knowledge. Realize effective personalized recommendation, so as to improve the satisfaction of online clothing shopping [16]. Yuan et al. proposed a method based on perceptual engineering (PE) and interactive genetic algorithm (IGA), which can effectively obtain a satisfactory color scheme [17]. Wang et al. solved the fuzziness and uncertainty of customer demand in product configuration through the analysis method based on grey rough model [18]. Tan et al. used analytic hierarchy process and grey relational analysis to evaluate and implement environmental protection product design [19]. Song et al. analyzed and ranked the design parameters of alternative solutions by combining benchmarking and quality function deployment methods in the improved fuzzy analytic hierarchy process [20].

To sum up, it can be seen that the use of big data can improve the innovation ability of industrial design, but it is difficult to process unstructured data, there are many applications of perceptual engineering in product color matching, there is a lack of intuitive visual display, and there are few relevant research data obtained from user demand evaluation. These problems are the difficulties of product design in manufacturing industry, which need to be further explored and studied.

### 3. Big Data-Driven Product Innovation Design Modeling and System Construction

*3.1. Product Innovative Design and Perceptual Engineering Method Based on Deep Learning.* With the development of

deep learning technology in recent years, significant research progress has been made in many fields by using its powerful feature of automatic learning from data itself. This paper presents a product intelligent design method based on deep learning. The specific work includes two parts; the first part is the research on product image recognition model based on convolutional neural network. The model can automatically identify the specific product image of the product picture. The second part is the research of product emotional intelligent design model based on generative antagonism neural network. The model can automatically generate a large number of product design samples. In order to improve the image quality generated by the model in manufacturing product design and control the content of the generated image, this paper uses image big data for product innovation design. Use perceptual engineering to improve user satisfaction, and transfer image content and style through neural style transfer. In the KENPI method, firstly, the mapping model is constructed to determine the field of the product. Taking the floor sweeping robot as an example, the perceptual words related to the shape and color of the floor sweeping robot are collected and sorted, and the product semantic space is established. The structural elements of products are analyzed by morphological analysis, and then the relevant attribute parameters are obtained. Three description dimensions are obtained to construct the product attribute space. On this basis, the BP neural network model is established. The BP neural network is divided into three layers: input layer, hidden layer, and output layer. The number of input layers and neurons of the model are determined according to the type of product parameters, and the product parameters include five items such as handle and symmetry axis. Therefore, the number of input layers and neurons of the model are 5, and the output layer is 3 description dimensions. The number of neurons in the hidden layer is determined by trial and error method, and the relevant mathematical expression is

$$p = \sqrt{n+q} + z. \quad (1)$$

In (1), the input layer, hidden layer, and output layer are set to  $n$ ,  $p$  and,  $q$ , respectively,  $z$  represents the empirical value, and  $1 \leq z \leq 10$ . Repeated experiments were carried out many times to determine the number of neurons in the hidden layer. The training sample set is used to train the model and then applied to the test set. A neurostyle migration (NM) model was established. The model structure is shown in Figure 1.

The NM model is divided into three parts: encoder, adaptive instance normalization (AdaIN), and decoder. In the encoder, the visual geometry group (VGG) 19 network trained in advance is used. The training data set is ImageNet data set, and the image features are detected through VGG-19 network. The AdaIN layer is used to normalize the content map, align the mean and variance of all feature maps contained in the content map, and match the mean and variance of all feature maps contained in the style map. The mathematical expression is shown as follows:

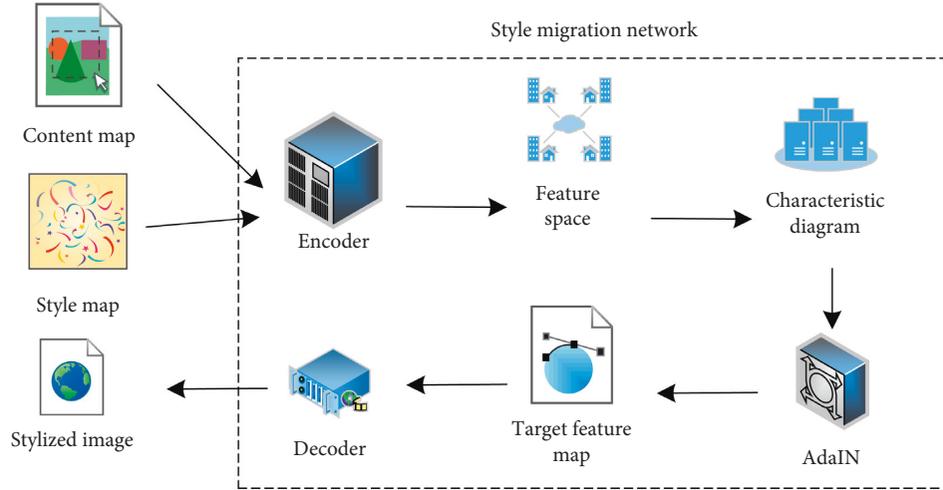


FIGURE 1: NM model structure.

$$t = A da IN(f(c), f(s)) = \sigma(f(s)) \left( \frac{f(c) - \mu(f(c))}{\sigma(f(c))} \right) + \mu(f(s)). \quad (2)$$

In (2),  $t$  represents the target picture,  $f$  means the encoder, set the content map and style map to  $c$  and  $s$ , respectively,  $\mu$  means the mean, and  $\sigma$  means the variance. In the decoder, the feature space is converted to the image space, and the resulting image has stylized characteristics. Its mathematical expression is as follows:

$$T(c, s) = g(t). \quad (3)$$

In (3),  $g$  means decoder and  $T(c, s)$  represents stylized image. The network structure of the decoder has a symmetrical relationship with the encoder. The weight parameters of the network are trained to minimize the loss function of the network. The expression of the correlation function is shown as follows:

$$\begin{cases} L = L_c + L_s, \\ L_c = \|f(g(t)) - t\|_2, \\ L_s = \sum_{i=1}^K \|\mu(\varphi_i(g(t))) - \mu(\varphi_i(s))\|_2 + \sum_{i=1}^K \|\sigma(\varphi_i(g(t))) - \sigma(\varphi_i(s))\|_2. \end{cases} \quad (4)$$

In (4),  $L$ ,  $L_c$ , and  $L_s$  represent loss function, content loss, and style loss, respectively,  $\varphi$  represents VGG-19 model used by encoder, the number of convolution layers of the model is set to  $K$ , and  $\varphi_i(s)$  represents the activation value of the style map at the  $i$  th layer of VGG-19 model. The semantic difference (SD) method for users is used to evaluate the semantics of the product style map generated by nm model. On the one hand, the semantic features of the product style map are based on the product feature semantics and the associated implicit semantics on the basis of the case base. An extension clustering mapping set based on product

graphical semantics is established. On the other hand, mining case-based design rules and building a case-based reasoning design rule database are done. The modeling design situation driven by graphic semantic clustering and design rules is constructed to realize product modeling design based on case-based reasoning. In the selection of style map, the image selection standard is the color with similar wavelength. The product form is not only the carrier of the product's physical property (this object but not others) but also the carrier of the product's aesthetic function (the symbolic meaning of the product). The sum of these information of the product is what the product wants to convey, that is, the semantics of the product. Therefore, product semantics is the carrier of product form. If the carrier is high, product semantics will not exist, that is, product form is the basis for the existence of product semantics.

The original product innovation design relies heavily on experts and is limited by the number of investigations and data timeliness. For this, this paper puts forward the perceptual engineering of online review data-driven (ORDD), which includes four parts: perceptual word collection and mapping model. Through the online review data-driven method, a large number of perceptual word data about product reviews are collected and processed and analyzed accordingly, which establishes the relationship model between user requirements and product design. Among them, the obtained data will be mixed with a lot of noise data, which is processed by flattering word segmentation. Compared with other Chinese word segmentation systems, the effect of flattering word segmentation is good, as shown in Figure 2.

As can be seen in Figure 2, the effect of stuttering segmentation is relatively the best, with the highest average accuracy of 92.16%. Then, word segmentation and part of speech tagging are carried out on the comment data of online comments, and word vector training is carried out. Establish product element space and product semantic

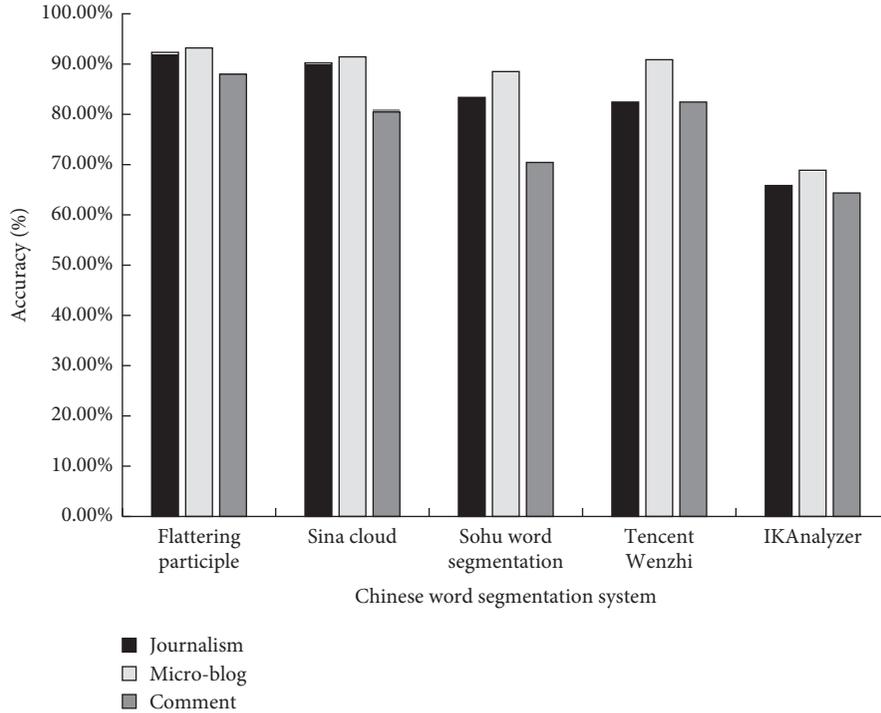


FIGURE 2: Accuracy of Chinese word segmentation system.

space. In the perceptual word acquisition method of product semantic space, combine word frequency with EPA to obtain TF-EPA method. Perceptual words are selected through three steps: adjective acquisition, similar adjective grouping, and word frequency statistics. By judging the emotional tendency of perceptual words based on the emotional dictionary, the relevant judgment results are obtained through the synonym forest. Synonyms are mostly used to accurately reflect the subtle differences between things. It precisely expresses people’s feelings and attitudes towards objective things, or it is constantly created to meet the needs of various styles of writing. To master the use of synonyms, the key is to distinguish the microdifferences between synonyms. Using degree adverbs, we can know the emotional intensity of polar words and the corresponding intensity score after calculation. Among them, the expression of emotional tendency of perceptual words is shown as follows:

$$EO(\text{word}) = (EP, EI). \quad (5)$$

In (5),  $EP$ ,  $EO$ , and  $EI$  represent emotional polarity, emotional tendency, and emotional intensity, respectively,  $EO(\text{word})$  represents emotional unit,  $EP \in (-1, 1)$  and  $EP$  represent negative emotion when  $-1$ , and  $EP$  represent positive emotion when  $-1$ . After summarizing  $EO(\text{word})$ , we can get the perceptual evaluation of the text and the perceptual evaluation value of relevant perceptual words. Using three-layer BP neural network, the product parameters are connected with perceptual evaluation, and a mapping model is constructed to predict the perceptual evaluation values of perceptual word pairs related to product quality, aesthetics, weight, and so on.

3.2. *Personalized Decision-Making of Product Design Scheme and Construction of Auxiliary System.* The alternatives of product innovative design are sorted and selected from the perceptual point of view. This paper combines TOPSIS method, KE method and GRAMethod to form the KE-GRATOPSIS method and obtains multi criteria decision-making (MCDM). This decision can consider the user preference, accurately sort the alternatives, and select the scheme that meets the user’s needs. In this process, grey relational analysis and TOPSIS (Grey relational analysis and TOPSIS, GT) based on grey correlation is involved. The KE-GRATOPSIS method mainly includes three parts. Firstly, the perceptual evaluation system of products is established, and the implementation method is the combination of the TF-EPA method and analytic hierarchy process. Then the subjective weight is obtained through the analytic hierarchy process, and the realization steps are divided into three steps. Firstly, the index judgment matrix  $O$  is established, as shown in (6), and each element is assigned through the scale of 1–9.

$$O = \{o_{ij}\} = \begin{bmatrix} o^{11} & o^{12} & \dots & o^{1j} \\ o^{21} & o^{22} & \dots & o^{2j} \\ \vdots & \vdots & \ddots & \vdots \\ o^{i1} & o^{i2} & \dots & o^{ij} \end{bmatrix} \quad (i, j = 1, 2, \dots, n). \quad (6)$$

In (6),  $n$  represents the number of elements,  $i$  and  $j$  represent elements, and  $o_{ij}$  represents the importance of element  $i$  to element  $j$ .  $o_{ij} = 1/o_{ji}$ , when  $i = j$ ,  $o_{ij} = 1$ . Solve the weight value and the maximum eigenvalue, represent the eigenvector according to  $Ow = \lambda_{\max}w$  and  $w$ , and calculate the weight of the eigenvector by using the square root

method to obtain the maximum eigenvalue, as shown in the following equation:

$$\lambda_{\max} = \sum_{i=1}^n \frac{Ow_i}{nw_i} (i, j = 1, 2, \dots, n). \quad (7)$$

In (7),  $n$  is the index number,  $w_i$  is the eigenvector, and  $\lambda_{\max}$  is the maximum eigenvalue. Conduct consistency test to check the rationality of the weight obtained. See the following formula for its calculation formula:

$$CR = \frac{CI}{RI} = \frac{\lambda_{\max}}{(n-1)RI}. \quad (8)$$

In (8), set the average random consistency index to  $RI$ ,  $n$  represents the order of the matrix, and set the consistency proportion to  $CR$ .  $CR < 0.1$  means that the judgment matrix is reasonable, otherwise adjust the judgment matrix. Among them, the average random consistency index is shown in Figure 3.

In Figure 3, with the increase of matrix order, the average random consistency index value is also increasing. After the judgment requirements are met, the weight vector of the index is obtained, and its formula is shown as follows:

$$W_1 = \{w_j, \quad j = 1, 2, \dots, n\}. \quad (9)$$

In (9),  $W_1$  and  $w_j$  represent the weight vector of the index factor. The perceptual decision matrix  $H$  is established, which is equivalent to the initial decision matrix. The perceptual decision matrix  $B$  is defined based on the user preference ( $U = \{U_j, j = 1, 2, \dots, n\}$ ). Its mathematical expression is shown as follows:

$$\left\{ \begin{array}{l} B = \{b_{ij}\} = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ h_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix} (i = 1, 2, \dots, m, j = 1, 2, \dots, n), \\ b_{ij} = N - |U_j - h_{ij}| (i = 1, 2, \dots, m, j = 1, 2, \dots, n). \end{array} \right. \quad (10)$$

In (10),  $i$  and  $j$  represent the  $i$  th alternative and  $j$  th index,  $b_{ij}$  represents the perceptual decision value,  $N$  represents the scale value of SD scale, and  $N = 7$ . The objective weight is calculated by entropy weight method. The input data is perceptual decision matrix  $B$ . The matrix is normalized to obtain the weight vector of index factors and the objective weight  $W_2$  of attributes:

$$\left\{ \begin{array}{l} w_j = \frac{d_j}{\sum_{j=1}^n d_j} (j = 1, 2, \dots, n), \\ W_2 = \{w_j, j = 1, 2, \dots, n\}. \end{array} \right. \quad (11)$$

In (11),  $d_j$  represents the information utility value. It can reflect the consistency of schemes in the  $j$  th attribute. The subjective weight and objective weight are combined to obtain the comprehensive weight, that is, the optimal equilibrium weight. Form the weight value into a weight set,

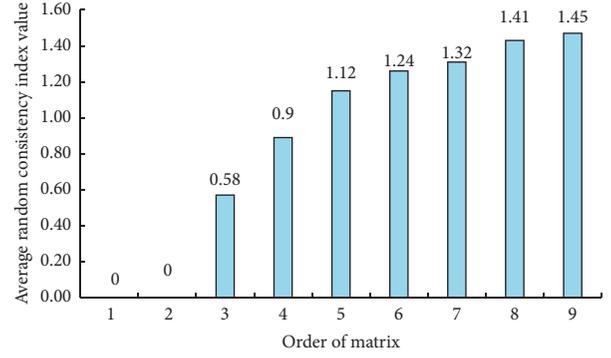


FIGURE 3: Average random consistency index.

optimize the weight coefficient  $\alpha_k$ , minimize the deviation between the possible weight vector  $w$  in the weight vector set and any weight vector  $w_k$ , and finally obtain the optimal equilibrium weight  $w^*$ :

$$w^* = \sum_{k=1}^L \alpha_k w_k^T (k = 1, 2, \dots, L). \quad (12)$$

In (12),  $\alpha$  represents the optimized weight coefficient,  $L$  represents the number of types of weight value, and  $w_k^T$  represents transpose. The GT method sorts the alternatives, takes the perceptual decision matrix as the input data of the method, and carries out standardized processing, so as to eliminate the influence of dimension on the decision results. Establish the weighted normalized decision matrix and determine the positive and negative ideal solution:

$$\left\{ \begin{array}{l} z_j^+ = \max z_{ij} (i = 1, 2, \dots, m, j = 1, 2, \dots, n), \\ z_j^- = \min z_{ij} (i = 1, 2, \dots, m, j = 1, 2, \dots, n), \\ A^+ = (z_1^+, z_2^+, \dots, z_n^+), \\ A^- = (z_1^-, z_2^-, \dots, z_n^-). \end{array} \right. \quad (13)$$

In (13),  $z_j^+$  and  $z_j^-$  represent the elements in positive ideal solution  $A^+$  and negative ideal solution  $A^-$ , respectively. Calculate the distance, grey correlation coefficient, and grey correlation degree between the positive and negative ideal solutions of the alternative scheme of each product innovative design, and the comprehensive value is shown as follows:

$$\left\{ \begin{array}{l} s_i^+ = \beta \frac{D_i^+}{\max(D_i^+)} + \gamma \frac{v_i^+}{\max(v_i^+)} (i = 1, 2, \dots, m), \\ s_i^- = \beta \frac{D_i^-}{\max(D_i^-)} + \gamma \frac{v_i^-}{\max(v_i^-)} (i = 1, 2, \dots, m). \end{array} \right. \quad (14)$$

In (14),  $D_i^+$  and  $D_i^-$  respectively represent the distance between the positive and negative ideal solutions of the alternative scheme of each product innovative design,  $v_i^+$  and  $v_i^-$  respectively represent the grey correlation degree,  $s_i^+$  and  $s_i^-$  represent the comprehensive value,  $\beta$  represent the influence coefficient of  $D_i^+$  and  $D_i^-$  on the comprehensive value, and  $\gamma$  represent the influence coefficient of  $v_i^+$  and  $v_i^-$

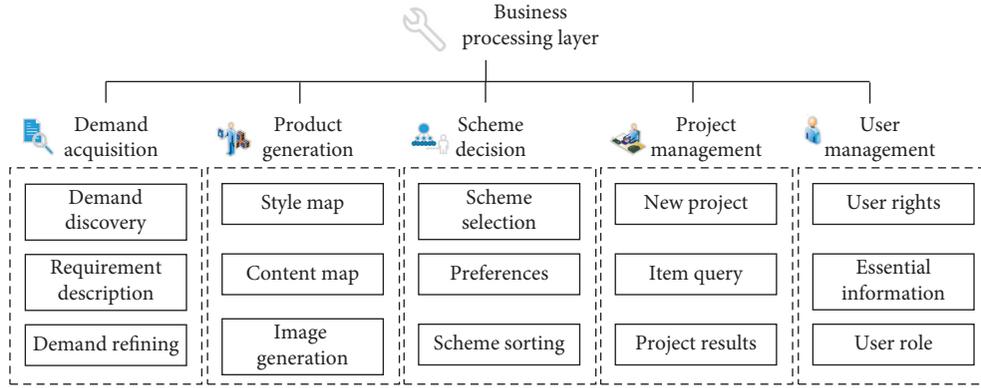


FIGURE 4: Functional structure of business service layer.

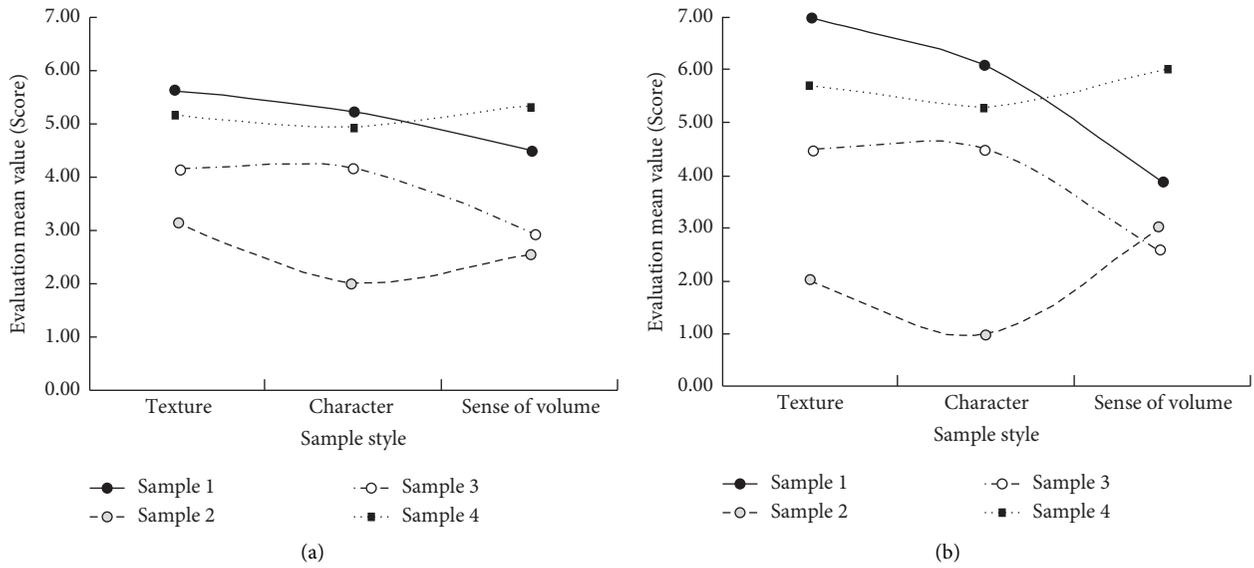


FIGURE 5: Evaluation mean value of samples (a) before migration and (b) after migration.

on the comprehensive value.  $\beta, \gamma \in [0, 1]$ , and  $\beta + \gamma = 1$ . Calculate and sort the relative closeness  $C_i$ , detect the degree of approach  $A^+$  and distance  $A^-$  of the scheme target  $A_i$ , and sort the alternative schemes on this basis. The mathematical expression of the relative closeness  $C_i$  is shown as follows:

$$C_i = \frac{s_i^+}{s_i^+ + s_i^-} \quad (i = 1, 2, \dots, m). \quad (15)$$

In (15), when  $A_i$  is closer to  $A^+$  and farther away from  $A^-$ , the value of  $C_i$  is closer to 1, and the alternative with the largest  $C_i$  is selected as the optimal scheme. Establish an auxiliary system for product innovation design. The system includes user layer and business service layer. The modules in the business logic layer contain all the functional algorithms and calculation processes required by the system. And interact with the data access layer and presentation layer. In the abstract, the business logic layer deals with the business related parts. Generally speaking, the business layer includes a series of execution and data operations. The data access layer is a code class library that provides access to data

located in a persistent container. In hierarchical design, all the work of reading or writing data from the media belongs to the task of this layer. The functional structure of business service layer is shown in Figure 4.

The business service layer includes five system functions such as demand acquisition and scheme decision-making. This layer includes all algorithms and calculations of the system. In the requirement acquisition function, it is divided into requirement discovery, requirement description, and requirement refinement. In the scheme decision-making function, it is divided into scheme acquisition, preference setting, and scheme sorting. It is mainly divided into three levels: (1) data access layer mainly refers to the operation layer for nonoriginal data (in the form of data storage such as database or text file), rather than original data. That is to say, it is an operation on the database, not data. Specifically, it provides data services for the business logic or presentation layer. (2) Business logic mainly refers to the operation of specific problems, and can also understand the operation of paired data layers. For data business logic processing, if the data layer is a building block, the logic is the description and

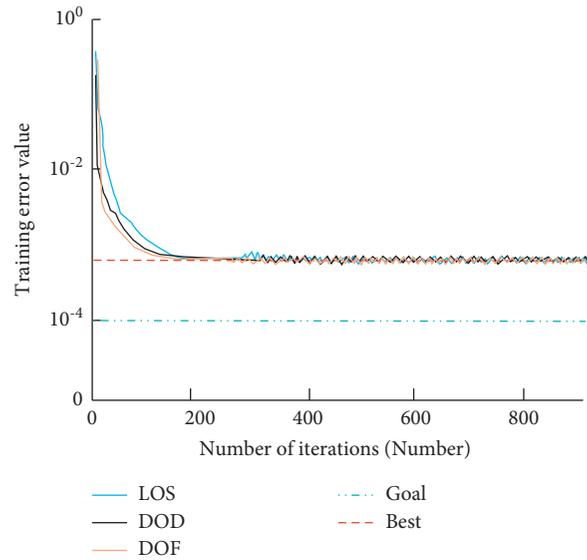


FIGURE 6: Training error curves of different perceptual phrases.

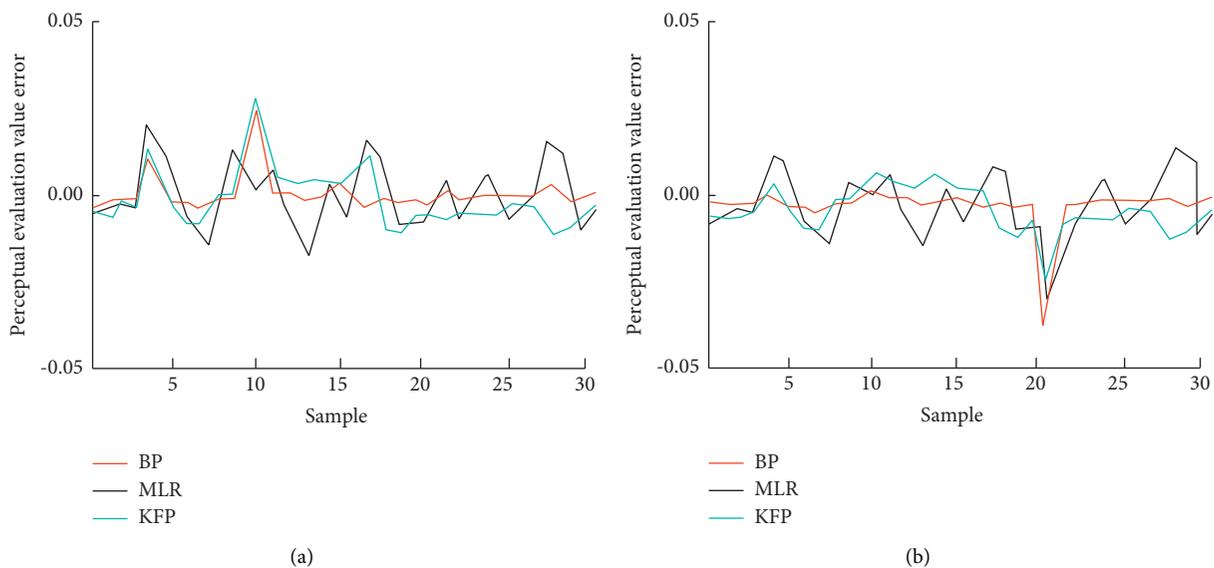


FIGURE 7: Prediction errors of different perceptual phrases by different methods. (a) DOD phrases and (b) DOF phrases.

construction of these building blocks. (3) Interface layer mainly represents the web mode. No matter how the logic layer and presentation layer are defined and changed, the logic layer can provide services perfectly.

In addition to the system architecture design, the database design, development, and operation environment are also carried out to ensure the normal and effective operation of the system.

#### 4. Application Analysis of Product Innovation Design Assistant System Based on Big Data

*4.1. Nm Model and Analysis of Perceptual Engineering Results.* This paper analyzes the migration result style of the NM model. Taking the sweeping robot as an example, four types

are selected as samples, the attribute parameters are obtained, and they are input into the trained BP neural model. The style images corresponding to the sample style semantics are selected, which are gorgeous, simple, publicized, low-key, small, and thick. These style images and sample images form a group and are input into the NM model, let 35 users evaluate the graph before and after the sample migration, and get the evaluation mean graph, as shown in Figure 5.

In Figure 5, the texture, character, and volume of the four samples changed in varying degrees before and after migration. Before migration, the mean value of texture evaluation of sample 1 was the highest; after migration, the average texture evaluation of sample 1 was 6.89 points, 3.79 points higher than that of sample 2. After the migration, the mean value of volume sense evaluation of

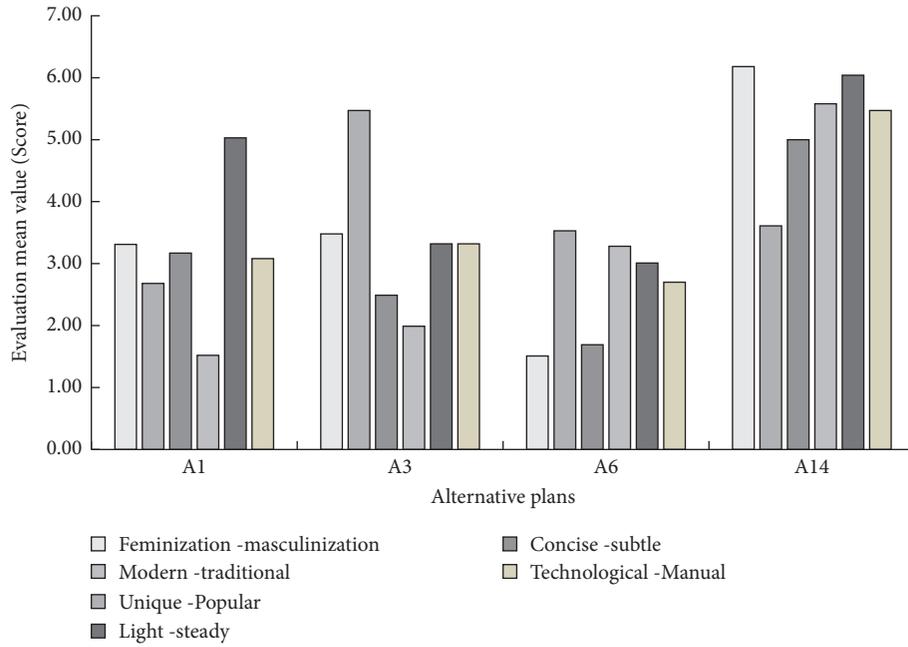


FIGURE 8: Evaluation results of some alternatives.

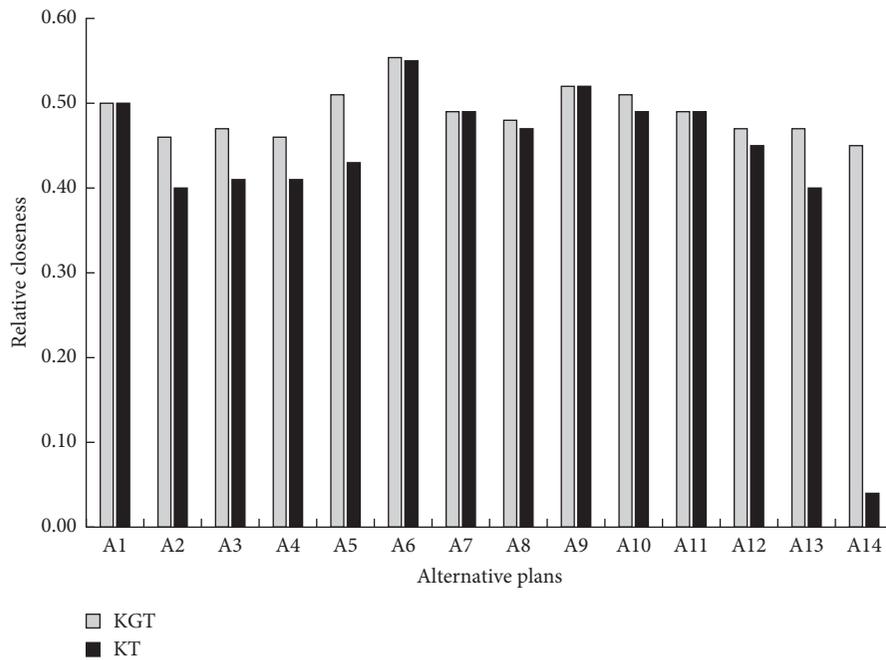


FIGURE 9: Relative closeness of alternatives under two methods.

sample 4 increased by 0.59 points, which can be seen that the “thick” semantics of sample 4 has been enhanced. Collect 200 sample product data, take 170 samples as the training set, and input them into the trained BP neural model. After feedforward calculation, the training error change curve of perceptual phrases is obtained. These phrases are large/small (LOS phrase), easy/hard (DOD phrase) and smooth/slow (DOF phrase). The results are shown in Figure 6.

In Figure 6, the training errors of different perceptual phrases vary to some extent. With the increase of the number of iterations, the error values of the three perceptual phrase models continue to decrease and gradually approach the optimal value. When the number of iterations is 890, the error value of LOS model reaches the minimum, and the optimal value of model training is 0.00067. It is 0.00028 lower than the optimal value of DOF model training. The DOD model reaches the optimal training value faster than

the DOF model, and the number of iterations is 920. The prediction errors of BP neural network, multiple linear regression (MLR), and Kalman filter prediction (KFP) model prediction methods on DOD phrases and DOF phrases are studied. The results are shown in Figure 7.

In Figure 7, under different prediction methods, the prediction errors of different perceptual phrases are different, and the errors in different verification samples are also different. From the broken line of subgraphs a and b, the prediction error broken line corresponding to BP neural network is relatively more gentle, and the prediction error broken line corresponding to MLR fluctuates the most. In subgraph b, the average absolute value of DOF phrases under BP neural network is 0.0706, which is 0.0318 lower than the average absolute value of phrases obtained by the MLR method.

**4.2. Analysis of Personalized Decision Results of Product Design Scheme.** The KE-GRA-TOPSIS method proposed in this paper is verified. Taking the electric drill as an example, the criteria and indicators of perceptual evaluation of electric drill are determined according to the TF-EPA method. It is divided into six criteria such as gender and acceptance, and each criterion contains a pair of perceptual words. 14 options are selected. The decision-making preference is masculine, the acceptance degree is the general public, it is a simple modern and lightweight electric drill, and the technical feature is general science and technology. That is, the preference of decision makers is  $U = [7, 5, 2, 3, 2, 3]$ . The KE-GRA-TOPSIS method is used to rank the alternatives. Based on the number of evaluation copies of 14 alternatives by 35 subjects, some evaluations can be obtained, as shown in Figure 8.

In Figure 8, the subjects' evaluation mean values of different criteria for different alternatives are different. The average score of traditional stable index of A14 scheme is 5.58 points, which is 2.30 points higher than that of A6 scheme combining perceptual engineering with TOPSIS to form the KT method, which is used as the comparison method of the KE-GRA-TOPSIS method. Based on the evaluation results, relevant calculations are carried out to obtain the relative closeness of the alternatives under the two methods. Some results are shown in Figure 9.

In Figure 9, the relative closeness of different alternatives under the two methods is different. From the histogram, it can be seen that the A6 scheme has higher relative closeness than other schemes under the two methods. According to the criterion score, it can be seen that the A6 scheme is consistent with the preference of decision makers and the prediction is accurate. The relative closeness of A6 scheme under the KE-GRA-TOPSIS method is 0.57, which is 0.02 higher than the KT method, indicating that the KE-GRA-TOPSIS method is better than the KT method.

## 5. Conclusion

This paper introduces image big data, establishes nm model by using BP neural network and Kenpi technology, and generates style map. Through the data-driven method of

online comments, the product attribute parameters are obtained, the product element space and product semantic space are established, and the perceptual evaluation is carried out. The KE-GRA-TOPSIS method is formed by combining the TOPSIS method, perceptual engineering and grey rule association to accurately sort and select alternatives, establish a product innovation design auxiliary system based on big data, and verify and analyze the research method. The results show that in the migration results of nm model, the texture of sample 1 after migration is 6.89 points, which is 3.79 points higher than that of sample 2. After migration, the average value of volume sense evaluation of sample 4 increased by 0.59 points. It can be seen that the "thick" semantic of sample 4 has been enhanced, and the image quality of sample 4 has been improved. When the number of iterations is 890, the error of service level model reaches the minimum, and the optimal value of model training is 0.00067. The average absolute value of phrases under BP neural network is 0.0706, which is 0.0318 lower than the average absolute value of phrases obtained by the MLR method. Among the different alternatives, the KE-GRA-TOPSIS method has the highest relative closeness in the A6 scheme, which is the best alternative and conforms to the preferences of decision makers. This article can also improve and perfect the types and product design methods of big data, and expand the application scope of big data.

However, in the innovative design of manufacturing products, the image quality generated by this model is poor, and the content in the generation process is uncontrollable. User preference is not considered, and there are problems such as small amount of research data and poor timeliness of data. Further elaboration and analysis are needed in the future research and analysis process.

## 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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