

Daily Ceramic Product Design Method Based on Optimized BP Neural Network Model and Kano Model

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Abstract

The demand for and design of daily ceramic products design tools is one of the application With the continuous development of society, the demand for daily ceramic product design tools is increasing, among which Back Propagation neural network (BPNN) and Kano model are widely used in the design field. This paper aims to optimize these two models and explore the methods of daily ceramic modeling design. Firstly, this paper summarizes the data and technology of daily ceramic design. Secondly, the demand of ceramic products is reclassified by Kano model, and the BPNN and Kano model are defined and optimized. Finally, the feasibility and effectiveness of this method are verified by simulation experiments. The results show that: (1) Consumers are more interested in flower and plant patterns, accurate pattern printing and custom pattern selection. In addition, consumer sensitive demand items are divided into 9 high sensitive demand items and 6 low sensitive demand items. (2) The error value ranges from 0.02 to 0.06 without using the order of magnitude normalization, but the error value ranges from 0.01 to 0.04 after using the order of magnitude normalization. This means that the performance of the model has been significantly improved by using order of magnitude normalization. (3) The perceptual evaluation values of the first group of four representative samples of ceramic products are 5.23, 4.89, 3.76 and 3.75 respectively. The perceptual evaluation values of the second group of descriptive words are 2.98, 5.76, 5.04 and 3.16 respectively. The perceptual evaluation values of the third group of descriptive words are 3.25, 6.64, 5.83 and 5.05 respectively. Different ceramic products have different evaluation values. Overall, the evaluation value of the first group is higher, indicating that the first group is more popular. The research in this paper provides some reference value for improving the quality of daily ceramic products.

Keywords: BP neural network, Kano model, daily ceramic product, data mining, requirement, satisfaction

I. Introduction

With rising living standards, a variety of ceramic products, such as tableware and kitchenware, have come into the public eye. These products evolve into new styles and types in response to changes in people's lifestyles. The range of uses for daily ceramics is gradually broadening as a result of the more varied decorative requirements for these items than in the past and the blurring of the lines between artistic and daily ceramics¹. Back Propagation (BP) neural networks and the Kano model have both been applied to ceramic product design as science and technology have advanced. Customers will like the created daily ceramic products thanks to the model used to identify their preferences and needs².

In the field of ceramic product design, previous research covers many aspects, including technical improvement for the matching accuracy of the depth discontinuity area of ceramic images, the correlation between the lifestyle of the new Small Office Home Office (SOHO) family and design of daily ceramics, and the multivariable dynamic customization recommendation model based on the attention mechanism. These research results provide different per-

spectives and technical support for ceramic product design, which has a certain direct impact on the importance and novelty of this paper in this field. The local stereo matching technology proposed by Zhu *et al.* (2021) solved the problem of matching accuracy of the depth discontinuity area on ceramic images, and provided new technical support for image processing in ceramic product design³. In addition, Bai *et al.* (2020) explored the relationship between the new SOHO family lifestyle model and daily ceramic design, which provided a useful reference for re-examining the aesthetic, relaxation and healing characteristics of product design⁴. Meanwhile, Dogan and Birant (2021) introduced the recommendation model of attention mechanism. Although the field was different, their method provided ideas for multivariable dynamic personalized design⁵. Finally, although the research of Kumar (2020) focused on the evaluation of teaching quality, the data mining tools and analysis techniques they use provided a reference for this paper to analyze the correlation between data and features in the field of ceramic product design⁶. Turukmane *et al.* (2022) used a new classification method based on deep learning to improve the performance of multi-spectral image processing technology, which was used to classify surfaces in multi-spectral

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satellite images. Wireless communication based on the Internet of Things (IoT) was monitored by using the Secure Locations Sensor Network Protocol (SLSNP). Multispectral satellite images were collected from developing and developed countries. After multispectral image data had been collected using the deep convolutional neural network (DCNN), the landmarks of multispectral images were estimated. This effectively identified resources in a specific location⁷. These studies have provided technical support and guidance for this paper, enabling this paper to deeply explore the design methods for daily ceramic products based on image processing, lifestyle requirements, personalized design, and data analysis. Therefore, this paper shows the novelty and importance of integrating these technologies and viewpoints, and provides a new perspective and method for the development of daily ceramic product design.

The above research covers many aspects, focusing on the design and use of daily ceramic products. Among them, the research methods using the BPNN and Kano models, and the algorithms and models applied to product design and data analysis are mentioned. These studies address the new ideas and technologies of ceramic product design, especially the exploration of the use of algorithms to optimize the product design and analysis process. In these studies, the emphasis is on using advanced technologies to improve the design and analysis of daily ceramic products, such as the use of the BPNN and Kano models to reclassify demand items, constructing the relationship model between product elements and perceived images, and verifying the correlation between product elements and image vocabulary. These methods provide researchers with a more comprehensive perspective to better understand the relationship between product design and user needs, and thus improving customer satisfaction and design quality of products. Compared with the existing research results, the innovation of this paper lies in the combination of the Kano model and BPNN model, which are applied to the design of daily ceramic products. This integration method provides researchers with a more comprehensive analysis perspective to better understand the relationship between product design elements, image vocabulary and customer satisfaction. In this way, this paper is committed to improving the design quality for daily ceramic products and meeting the needs of consumers more accurately. This comprehensive method has certain innovation and practical value for the field of daily ceramic product design.

II. Application of the BP network and Kano model in ceramic product design

Fundamentals of BP neural networks

BPNN is a common artificial neural network, which is used to simulate the signal transmission process among human brain neurons. It is mainly composed of an input layer, hidden layer and output layer. The input layer is used to receive data input from the outside. In the design of ceramic products, these inputs may be the consumer's description, evaluation or other related information. The hidden layer is the place where information is processed within the network. The neurons in the hidden layer trans-

form and process the input data to capture the complex relationship between the data. The output layer finally returns the final result of the network. BPNN learns the patterns and relationships between data through training. This training process is divided into two stages: forward propagation and backward propagation. Forward propagation means that data is transmitted from the input layer to the hidden layer and the output layer, and the network generates prediction results. Back propagation is used to compare the difference between the predicted results and the actual results, and the network adjusts the internal parameters to reduce the prediction error. This process is repeated, which enables the network to be continuously optimized and improve the accuracy of prediction. In the design of ceramic products, BPNN can be used to analyze consumers' preferences and demands, and predict the satisfaction or the importance of product characteristics. It can help designers better understand consumers' ideas and guide product design and improvement to better meet market demand.

BPNN is an important tool, especially in understanding consumer preferences and needs. It is a machine learning technology, which can identify a complex relationship between data and use it for prediction and classification. In the design of daily ceramic products, BPNN is used to analyze consumers' preferences and satisfaction with products. Specifically, the application of BPNN in this field is mainly reflected in the following aspects: (1) Consumer preference prediction: Based on training of the BPNN model, consumers' historical data, demand evaluation and other characteristics can be used to predict their preferences for different characteristics of ceramic products. This helps designers to ascertain more accurately the trend in consumers' preferences, and use this knowledge to guide the design and improvement of products. (2) Product characteristic optimization: BPNN can be used to analyze and optimize product characteristics. Through the study of consumer feedback data, people can determine which product features are valued by consumers and which features may need to be improved. This provides clues and directions for manufacturers to improve product design. (3) Market positioning and segmentation: With reference to the analysis of consumer preferences based on BPNN, market positioning and segmentation can be carried out more accurately. Different consumer groups may have different preferences for products. BPNN can help identify these differences and provide support for customized design and marketing. Through these applications, BPNN plays an important role in the design of daily ceramic products. It can not only help designers gain a deeper understanding of consumer demands, but also guide product design and market strategy to better meet the changing market demand.

Design of daily ceramic products

Although the term "daily ceramics" refers to pottery and porcelain, it also encompasses stoneware, earthenware, and porcelain. All everyday objects that are shaped, sculpted, and calcined clay and other natural minerals are together referred to as daily ceramics. People often use various



Fig. 1: Examples of new daily ceramic products.

Table 1: Vocabulary of ceramic modeling images.

Classification		Image Vocabulary Pair		
Product form	Tradition – Modern	Simplicity – Complexity	Ordinary – Strange	Compact – Atmospheric
Technology	Function - Decoration	–	–	–
Size Scale	Harmony - Contrast	–	–	–
Material type	Gorgeous - Simple	–	–	–
Color Matching	Simplicity – Colorful	Feminine – Cool and elegant	–	–

decorative techniques, such as cosmetic coating, coloring, and glaze, to beautify blank products and give them more spiritual qualities beyond their intended use. Ceramic art must be able to master the design sensibilities and material skills, the craftsmanship and aesthetics, and people’s imagination and modeling talent ⁸. Japanese ceramics, as well as those from China and other nations, are frequently used in daily life, but the majority of them are primarily utilized as eating utensils ⁹. Fig. 1 depicts a few current innovations in daily ceramic items.

Daily ceramics are ceramics made for everyday use, typically based on their practical qualities, and can be broadly categorized into tableware, tea sets, coffee sets, wine sets, kitchen utensils, and other items ¹⁰. Industrial porcelain (building ceramics, chemical stoneware, electric ceramics, and special ceramics), which can also be split into porous ceramics and dense ceramics according to different materials, is another type of porcelain that is available in addition to home porcelain ¹¹. The vocabulary of ceramic modeling images obtained by classifying the intentional vocabulary of ceramic design is shown in Table 1.

The demand classification of the Kano model for users of daily ceramic products

The Kano model plays an important role in product demand assessment, and its reclassification can be supported by deeper explanation and concrete basis. This classifi-

cation is based on the understanding and analysis of consumer demand, covering the priority and influence of different types of demand. The re-classification basis of this model usually includes a detailed analysis of consumer survey data ¹². This paper first collects a wide range of customer input, covering the requirements for various product features and functions. Then, these requirements are classified, and based on the degree of influence of different requirements on consumer satisfaction, they are divided into six categories: Q, A, R, I, M and O. These classifications are not only a simple summary of consumer demand, but also a comprehensive analysis result based on in-depth market research and customer feedback data ¹³. Specifically, the Q-type requirement is usually regarded as standard functions expected by customers, and the existence of these functions is necessary for improving product satisfaction. The A-type requirement covers those extra functions that can significantly improve customer satisfaction, and they are often innovative in product design. The R-type demand refers to a demand that consumers have not yet explicitly stated, but once realized, it will lead to an increase in satisfaction¹⁴. The I-type requirement refers to missing functions, and their implementation usually does not affect product satisfaction, but the lack of them may lead to dissatisfaction. M-type and O-type requirements indicate that consumers have nothing to do with or have low expectations for certain features or functions in

products. By reclassifying these requirements, manufacturers can more accurately understand the key features and functions of products, and accordingly establish product roadmaps to better meet market demand. This reclassification provides a deeper insight, enabling manufacturers to give priority to and rationally plan the characteristics and functions of products to enhance market competitiveness. The classified user requirements of Kano model are shown in Table 2.

Table 2: The classification of Kano model user requirements.

Character	Symbol meaning
Q	There is an error. Generally, it is impossible for the same customer to choose “satisfied” with the function of the ceramic product.
A	Customers will be surprised that the product has this function, which is an element of ceramic product identification.
R	Consumers do not want to use this pattern or technology in daily ceramic products.
I	This requirement item is optional. Whether the function is available or not has no impact on most consumers.
M	Basic needs.
O	Category of demand items to be valued.

Because the Kano model has two types of positive and negative problems, the user's satisfaction can be obtained by analyzing the classification of the meaning of the Kano model and the positive and negative problems¹⁵. The results are shown in Table 3.

Table 3: Comparison of Kano model results.

Reverse problem/forward problem	Satisfied	It should be	All right	Acceptable	Inadmissibility
Satisfied	Q	A	A	A	O
It should be	R	I	I	I	M
All right	R	I	I	I	M
Acceptable	R	I	I	I	M
Inadmissibility	R	R	R	R	Q

It is important to calculate the Better-Worse coefficient after doing a qualitative study of each requirement to determine the demand degree for each requirement using the Better-Worse coefficient analysis method¹⁶. Consumer happiness with daily ceramic products is represented by the Better coefficient when the Demand Item is included,

and Consumer Dissatisfaction with the Demand Item is represented by the Worse coefficient¹⁷. This is how the Better-Worse coefficient is determined:

$$S_{SI} = \frac{S_A + S_O}{S_A + S_O + S_M + S_I} \quad (1)$$

$$D_{DSI} = -\frac{S_M + S_O}{S_A + S_O + S_M + S_I} \quad (2)$$

$$\omega = S_R \sqrt{(S_{SI})^2 + (D_{DSI})^2} \quad (3)$$

S_{SI} stands for the Better coefficient. D_{DSI} stands for the Worse coefficient. S_A , S_O , S_M , S_I and S_R are the number of times the demand item is selected, and ω is the demand index. In the process of research, the Kano question-answering model mainly involves two aspects, one is the related demand of technology, and the other is the related demand of pattern. There are 15 demand items in total and they are numbered. The specific contents are shown in Table 4.

Table 4: Kano model requirement item content.

Requirement item number	Requirements item content
Y1	Beautiful design
Y2	Ceramic modeling
Y3	Custom graphics
Y4	Safe and efficient production process
Y5	Accurate pattern printing
Y6	Processing parameters
X1	Complete design concept
X2	Reasonable pattern layout
X3	The pattern has valuable connotation
X4	Flower pattern
X5	Pattern of attracting wealth and treasure
X6	Siheruyi pattern
X7	Traditional dragon and tiger pattern
X8	Animation pattern
X9	New art patterns

Analysis of daily ceramic materials based on the BP neural network model

The BP neural network is now the most extensively used neural network model because it is one of the multi-layer feedforward networks based on error back propagation training¹⁸. The following two components make up the majority of this network model: The first is the effective spread of knowledge. The rearward propagation of mistakes is the second¹⁹. The network input layer is primarily in charge of efficiently obtaining input data from the outside world and swiftly transmitting it to the intermediate layer. The middle layer's primary duty as one of the internal information processing layers is to efficiently convert the information it receives²⁰. Meanwhile, the middle layer can be developed in the direction of a single hid-

den layer structure or, of course, the multi-hidden layer structure can also be taken into consideration²¹ depending on the requirements of information change ability. It will transmit the pertinent data sent by the middle layer to the output layer as a hidden layer for further processing. The information will now be processed by the output layer and returned to the outside world, marking the successful completion of a learning forward propagation process²².

If the actual output and the anticipated output do not match, the error will be introduced into the back propagation stage, where its ownership value will be fixed using the error gradient descent method, and it will then be returned to the input layer²³. This makes the forward and backward propagation process identical to the process of adjusting the weights of each layer, and it also makes it possible to think of it as a network's learning and training process²⁴. Until the output error of the network is decreased to a level that is acceptable or until a predetermined number of learning cycles have passed, this cycle is repeated²⁵. In fact, the BP network also belongs to the category of multi-layer neural networks. The model structure of the dual-layer BP neural network is shown in Fig. 2.

When adopting a linear transfer function, the output layer of a multi-layer BP network can take on any value. The BP neural network uses the elastic algorithm, the steepest descent method, the momentum algorithm, the variable learning rate algorithm, and the variable learning rate algorithm²⁶. The steepest descent method, also referred to as the steepest slope method, is an iterative procedure for estimating nonlinear regression model parameter least squares. The weights and thresholds are corrected when all the samples are entered and the total error is computed. Batch processing is the name of this corrective technique²⁷. The batch processing approach converges more quickly than the single processing method when there are many samples²⁸. The momentum BP algorithm is actually an algorithm based on gradient descent, which introduces momentum factor. The equation is as follows:

$$\Delta x(k+1) = \eta \Delta x(k) + \alpha(1 - \eta) \quad (4)$$

$$x(k+1) = x(k) + \Delta x(k+1) \quad (5)$$

In the equation, Δx is the change of information before and after, k is the number of iterations, η is the momentum factor, α is the learning rate, and x is the input information.

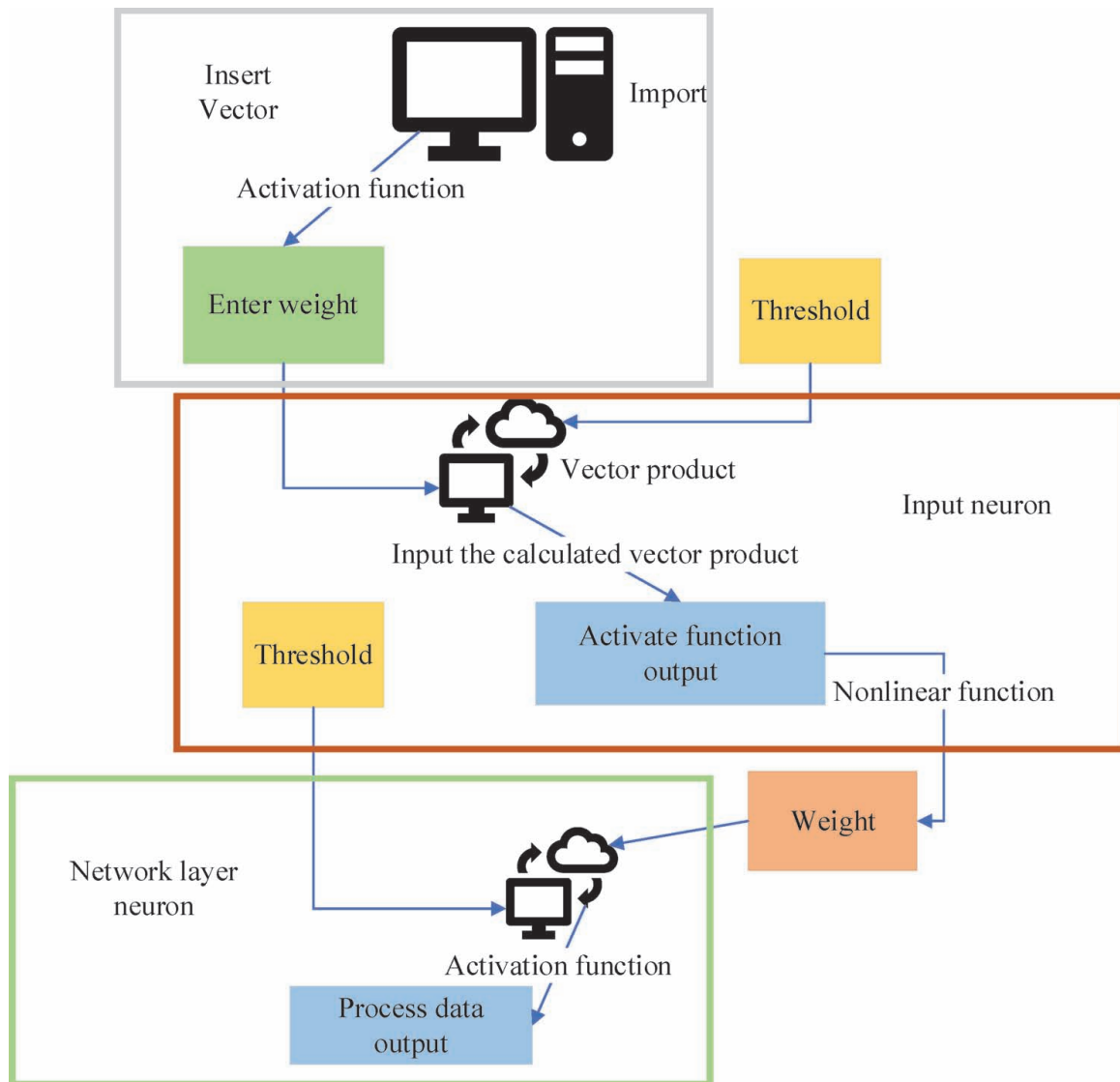


Fig. 2: Dual-layer BP neural network model.

Whether it is the steepest descent or momentum BP algorithm, its learning efficiency belongs to the constant category, and its value always remains unchanged. The performance of the algorithm is sensitive to the choice of learning rate. When the learning rate is too high, the algorithm may oscillate and become unstable²⁹. The convergence speed will be slow and the training period would lengthen if the learning rate is too slow. To pick the ideal learning rate before training, though, is impractical. In fact, the algorithm can be altered along the error performance surface and the learning rate can fluctuate with the training process³⁰. The learning step should be maximized, and the algorithm should become more stable, using a gradient descent method that adaptively changes the learning rate. According to the local error surface, the learning rate is modified³¹. Finally, the elastic algorithm's primary application is to entirely reverse the negative effects brought on by the gradient's amplitude. Due to the fact that the amplitude of the partial derivative will have no effect on the weight correction process, just the sign of the partial derivative is often used in this process. Currently, the correction process simply depends on the weight's correction value, which is often independent of the amplitude³². In the event that two iterations follow one another while maintaining the same gradient direction, the goal of increasing the correction value can be achieved by multiplying the correction value by the increment factor, while the

goal of reducing the correction value can be achieved by multiplying the correction value by the decrement factor in the event that the gradient direction is in the opposite direction^{33, 34}.

Daily ceramics can be categorized into four groups based on their internal structure and physical characteristics: feldspar porcelain, sericite porcelain, phosphate porcelain, and talc porcelain. Of these four groups, feldspar porcelain and sericite porcelain are the most widely used, and they are both used in daily ceramics. Phosphate and talc porcelain are mostly used for high-end everyday tea sets or ornamental art porcelain. According to the raw materials used, daily ceramics can be categorized into three groups: flux raw materials, non-plastic quartz raw materials, and plastic clay raw materials.

Optimization of the Kano Model and BP Neural Network Model

In order to further enhance the Kano model's decision-making assistance for subjective issues, it is necessary to investigate the relationship between the consumer satisfaction metric and a number of other parameters. Since this research has broad potential applications, it is necessary to enhance the Kano model's unique procedure. The major steps in this optimization process are to expand the categories of demand items and tighten the screening criteria. Fig. 3 depicts the precise procedure.

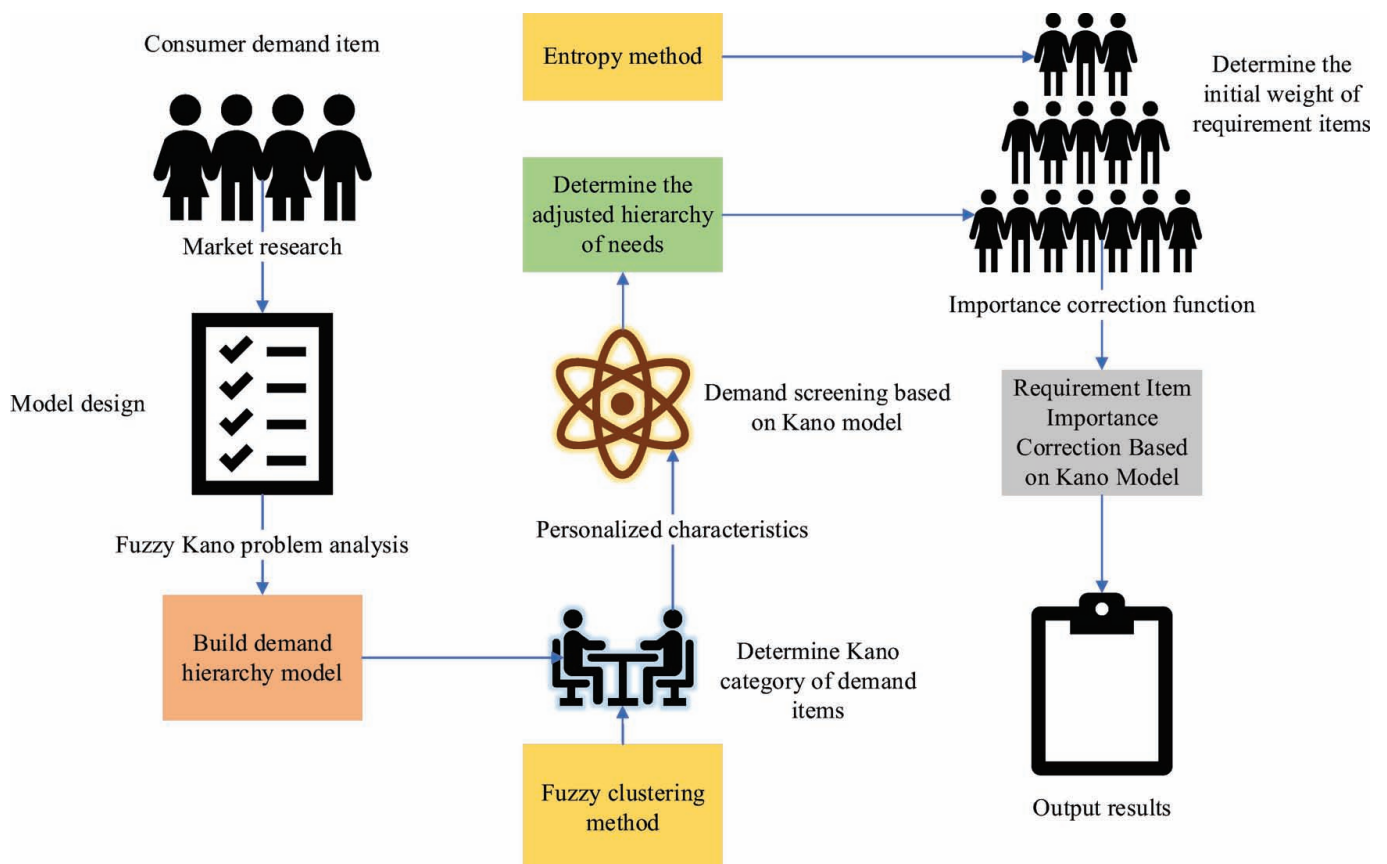


Fig. 3: Flowchart showing the optimized Kano model.

BPNN has many advantages, such as high classification accuracy, strong learning ability, robustness and fault tolerance to noise data, and associative memory ability. It can effectively approximate various nonlinear relationships and be used for feature extraction. However, the neural network method has obvious defects such as numerous parameter settings, long learning process and the possibility of falling into local optimal solution. Therefore, this paper focuses on data preprocessing as the most effective strategy to prevent these problems. In the process of optimizing the neural network model, this paper adopts a series of detailed strategies and methods. Firstly, for the data preprocessing stage, this paper emphasizes strict data cleaning measures to eliminate noise data and inconsistencies and ensure data quality and consistency. Secondly, in the data preparation stage, appropriate data conversion technology is used to ensure that the data is more accurate and reliable in the modeling process. In addition, according to the requirements of a specific model, data reconstruction and feature engineering are carried out to make the data closer to the actual application scenario and improve the interpretability and effect of the model. The implementation of these optimization strategies not only improves the stability, accuracy and generalization ability of the model, but also ensures the integrity and reliability of the data while improving the performance of the model. With these carefully designed optimization steps, this paper successfully meets the challenges of complex parameter adjustment and long learning process faced by the neural network method, making the model more robust and better adapted to different data situations. The successful application of these optimization strategies provides valuable method reference and experience accumulation for future related research. The data preprocessing flow of the optimized BPNN model is shown in Fig. 4.

It is very important to optimize the data preprocessing process of the BPNN model, which ensures the accuracy and reliability of data quality. The key factors of data quality usually include three aspects: missing or inconsistent data, noisy data with wrong attribute values, and incompleteness that only provides partial aggregated data. These problems often appear in practical applications, but they can be solved by effective data cleaning and processing methods. The incompleteness of data may come from many situations. For example, some information may be regarded as secondary information when it is registered in the market and is not included. In addition, for various reasons, relevant information may not be recorded, resulting in inconsistency with the recorded information, and may even be accidentally deleted. To remedy these situations, a powerful and accurate data cleaning program is needed to ensure the integrity and accuracy of data. This paper adopts a series of optimization strategies and methods to deal with data quality problems. Firstly, the data cleaning stage covers the identification and processing of missing data, erroneous values and abnormal values. Secondly, data filling and interpolation methods are used to complete the missing data and reduce the impact of incomplete data. In addition, data reconstruction and merging methods are adopted to ensure the integrity and consistency of datasets. The application of these detailed optimization strategies and methods not only improves the quality of data, but also lays a solid foundation for the accuracy and reliability of the model. These methods can effectively deal with the data quality problems in real life and provide reliable data support for model training and prediction. The successful application of these optimization strategies and methods provides valuable experience and technical guidance for future-related research.

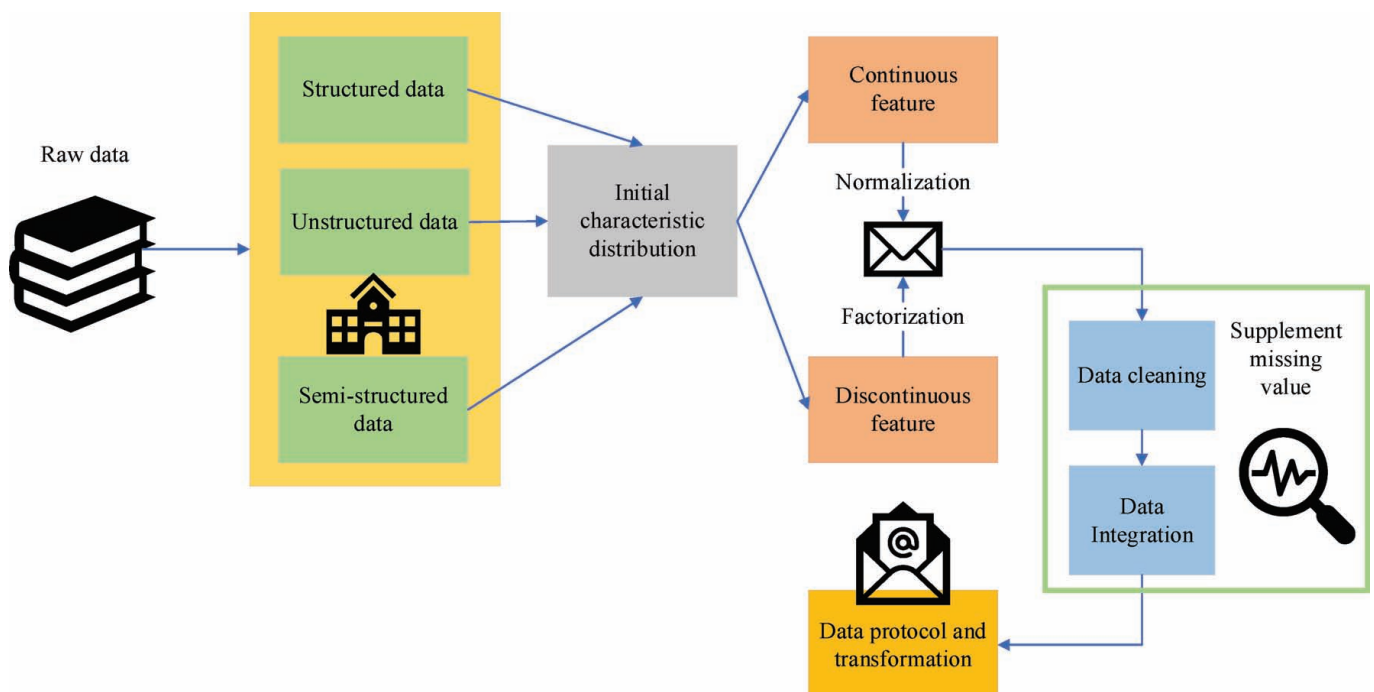


Fig. 4: Optimized BP neural network model data preprocessing process.

III. Experimental data design

The data used in the experiment comes from two main channels: Firstly, this paper collects the sales data of ceramic products from different regions, including sales volume, feature description and customer satisfaction. Secondly, based on the survey data of the Kano model, the survey object is the potential consumers of ceramic products to understand their preferences for the design characteristics of ceramic products. Data features: The dataset includes 500 sales records of ceramic products, covering product features, prices, sales areas and other information. Among them, 30 % of the data have some missing values, which are mainly concentrated in product feature description. In addition, there are 5 % outliers in the data, which needs to be processed in the data preprocessing stage. Kano model survey data: The survey covered 300 potential consumers and scored different ceramic product design elements. The data includes consumers' subjective evaluation of product design characteristics, which includes ceramic patterns, material texture, price and so on.

Data processing process: (1) Data cleaning: For sales data, the missing values and abnormal values are processed, and the methods of mean filling and eliminating abnormal values are adopted. The survey data of the Kano model are de-duplicated and invalid data are eliminated. (2) Data integration: The sales data and Kano model survey data are integrated and matched based on product feature description to create a comprehensive dataset including product sales and consumer preference scores. (3) Data simulation method: During the simulation of data, the changes in different consumers' preferences are considered, and the diversity of actual market feedback is simulated by randomly generating consumers' scores on specific design elements. (4) Experimental verification process: The dataset is divided into training set and test set with the cross-validation method, and the performance of the BPNN model is evaluated under different pretreatment conditions.

IV. Design and analysis of daily ceramic products based on BP optimization model and Kano model

Analysis on the results of consumer demand for daily ceramic products under the Kano model

The final 15 demand items identified by the model are assessed in positive and negative dimensions, and artificial intelligence (AI) is used to imitate customer behavior for tests. This is done in an effort to minimize the data pollution brought on by cognitive short-term inertia. Following statistics, Fig. 5 displays the pertinent technology demand results together with the associated Better and Worse coefficients.

Fig. 5 shows the distribution of demand for daily ceramics design. These requirements are classified into different categories according to their importance and satisfaction, and reclassified according to the Kano model. First, it is important to point out the key design requirements in daily ceramic products. Under the framework of the Kano model, the pattern printing and ceramic texture represented by Y1 and Y2 are classified as A-type requirements, that is, characteristics that are very important to consumers and expected to be satisfied in products. This means that these

two factors are regarded as standard requirements in daily ceramic products. On the other hand, the demand of Y3 and Y6 is classified as O-type, which means that consumers have low expectations for these features, but if they can be realized, they will improve product satisfaction. Therefore, considering these characteristics in the design stage may win additional competitive advantages for the product. Y4 and Y5 are classified as M-type requirements, which means that these two features are not particularly concerned or expected by consumers. In product design, the realization of these characteristics has little influence on product satisfaction. In the study of the Kano model, the better-worse coefficient is also used to judge the sensitivity of demand. Y1, Y2, Y3, Y5 and Y6 are classified as very sensitive, which means that consumers are very sensitive to changes in these characteristics. In contrast, the sensitivity of Y4 is low, which means that the change of this feature does not affect the satisfaction of consumers. This classification and sensitivity evaluation provide guidance for the design of daily ceramic products, and help manufacturers to know more clearly which characteristics are the priority of consumers, and how to weigh and consider these needs in product design. Fig. 6 displays the associated demand findings of the patterns along with the corresponding Better and Worse coefficients.

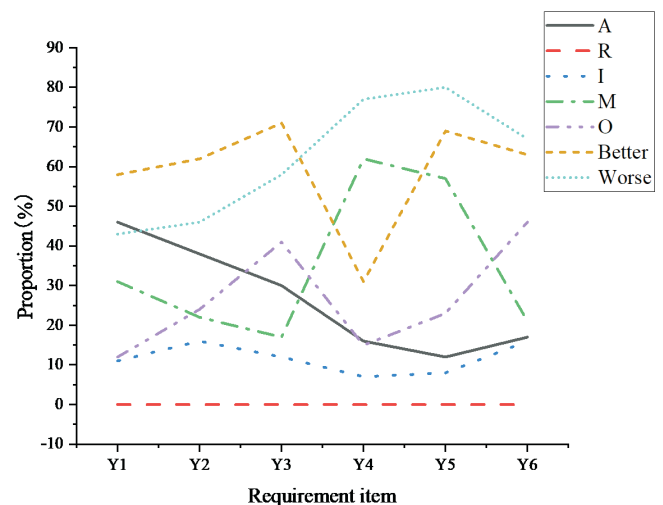


Fig. 5: Related demand results of technology and Better-Worse coefficient.

Fig. 6 shows consumers' demands for daily ceramic patterns, which are arranged according to their priorities. These requirements are reclassified under the Kano model and analyzed according to their attributes. Firstly, X4, X5, X7, X1, X9, X3, X6, X2 and X8 represent various pattern requirements for daily ceramic products. In the Kano model, these demands are reclassified according to consumers' attention and expected satisfaction. The attributes of X1 and X5 are classified as A-type, which means that consumers attach great importance to and expect these demands. These requirements include selecting and personalizing patterns, printing accurate patterns and using patterns from various sources. This means that these characteristics are very critical for the design of daily ceramics and attract consumers' attention. X2 and X8 are classified

as I-type requirements, indicating that consumers attach less importance to these features. These requirements include daily ceramic production methods, logical pattern arrangement and animation pattern style. These characteristics are not the focus of consumers' special attention in product design. X3 and X6 are classified as M-type requirements, indicating that consumers' attention to these requirements and expected satisfaction are relatively neutral and do not have a significant impact on product satisfaction. X4, X7 and X9 are classified as O-type requirements, indicating that consumers have low expectations for these requirements, but if they can be realized, they may improve product satisfaction. In addition, according to the better-worse coefficient, the demand is divided into several groups. X4, X5, X7 and X1 are identified as extremely sensitive demands, and consumers are very sensitive to changes in these demands. In contrast, X9, X3, X6, X2 and X8 are identified as low-sensitivity demands, and changes in these demands are unlikely to affect consumers' satisfaction. These classification results provide guidance for daily ceramic product design, and help manufacturers to better understand consumers' priorities and expectations in order to better meet market demand.

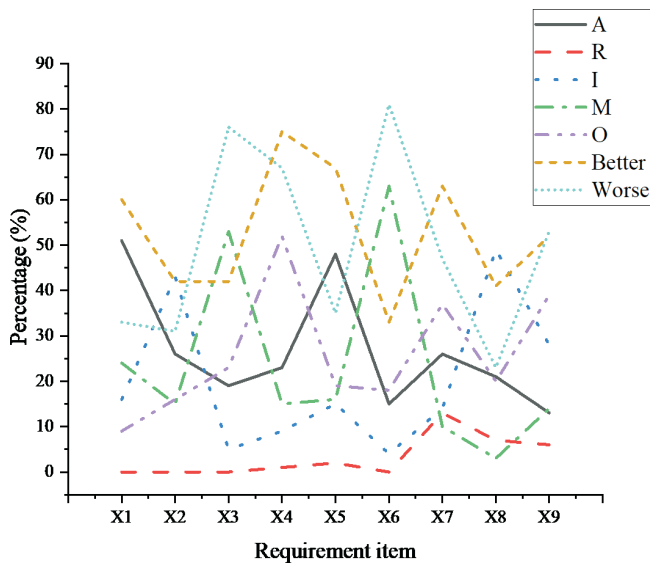


Fig. 6: Related demand results of patterns and Better-Worse coefficient.

Analysis results of BP optimization model for daily ceramic products

In the daily firing process of ceramics, different moisture and element contents in raw materials have an impact on the manufacture of ceramics. For example, when the water content is too high, insufficient firing time may lead to uneven patterns on the ceramic surface, while excessive carbon leads to darker color after firing, both of which should be taken into account. The University of California Irvine (UCI) dataset is a commonly used standard test dataset for machine learning, and it is a database for machine learning proposed by the University of California, Irvine. Dataset 1 is high-temperature firing data, which contains the content records of various mineral components and elements of ceramic samples at high temperature. High-tempera-

ture firing may lead to the crystallization, phase transformation and lattice arrangement of mineral elements, thus affecting the texture, strength and surface characteristics of ceramics. Dataset 2 is low-temperature firing data, which records the data of ceramic samples fired at low temperature. The dataset includes the content records of various mineral elements in ceramic samples at low temperature. Low-temperature firing may lead to a loose crystal structure of mineral elements, which affects the compactness and compressive strength of ceramics. Dataset 3 is different in water content, and the dataset includes the content records of various mineral components and elements of ceramic samples under different water content conditions. The change of water content may affect the temperature control and crystallization process of ceramics during firing, and then affect its texture, color and appearance. Dataset 4 is the data source of different firing time, and records the data of ceramic samples under different firing time conditions. This dataset includes the content records of various mineral elements in ceramic samples at different firing times. The change of firing time may lead to the change in crystal morphology and crystallinity of mineral elements and affect the uniformity and quality of ceramics. Dataset 5 is the content data of different components, and the dataset includes the content records of different mineral components in ceramic samples. The content of different components may affect the strength, color and surface characteristics of ceramics, such as the depth of color and the thickness of texture. Dataset 6 is the data of different glaze coating, and the dataset includes the content records of various mineral components and elements of ceramic samples under different glaze coating conditions. Different glaze coating methods may lead to different glossiness, wear resistance and antifouling properties of ceramic surface, thus affecting its appearance and practicality. In this paper, six groups of ceramic fired mineral data in UCI database are preprocessed, and the error between the pre-processed data and the actual value is calculated. Tetrafluoroethylene (TFE), ferrous oxide (FeO), carbon (C) and water content are the predicted data in this paper. The experimental results are shown in Fig. 7.

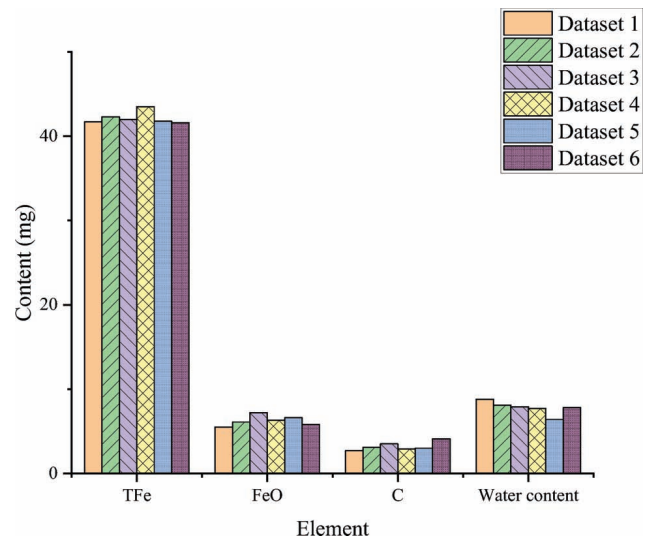


Fig. 7: Prediction results of the BP neural network optimization model.

Two different data processing strategies are compared and trained in the experiment. Data preparation without order-of-magnitude normalization is one type, which involves the experimental original data. Preprocessing the normalized data comes after another set of trials that include normalizing the original data by an order of magnitude. Table 5 displays the discrepancy between the actual number and the outcome that was projected.

Table 5: Error between predicted value and true value of BP neural network model.

Dataset number	The error between the predicted value and the real value of operation without using the order of magnitude normalization	Error between operation predicted value and real value using order of magnitude normalization
1	0.04	0.01
2	0.03	0.02
3	0.02	0.04
4	0.06	0.03
5	0.06	0.04
6	0.6	0.01

In the experimental group that does not use the order-of-magnitude normalization operation, there is a big error between the predicted value and the actual value through the learning of BPNN algorithm. The data in the table shows the error between the predicted value and the actual value in two different cases, one is when the order-of-magnitude normalization operation is not used, and the other is when the order-of-magnitude normalization is used. The error value ranges from 0.02 to 0.06 without using the order of magnitude normalization, while the error value ranges from 0.01 to 0.04 after using the order of magnitude normalization. This means that the performance of the model has been significantly improved by using order-of-magnitude normalization. In most cases, the error between the predicted value and the actual value is reduced after using order-of-magnitude normalization. For example, in dataset 1 and dataset 6, the error decreases from 0.04 and 0.60 to 0.01. This decrease may mean that the model predicts the actual value more accurately and improves the prediction accuracy. The operation of order-of-magnitude normalization plays a key role in reducing the error value, especially in dataset 6, the error is reduced from 0.60 to 0.01, which is a huge improvement. These improvements show that the optimization method has a significant impact on improving the model performance and reducing the error rate, especially when dealing with data with different numerical ranges, the use of order of magnitude normalization can better adapt to the training and prediction process of the model.

Analysis of ceramic modeling image vocabulary and product modeling satisfaction

Determination of output parameters of the neural network: (1) Sample selection: According to four representative ceramic samples and six groups of descriptive words selected in the second chapter, the representative samples are analyzed. T1 is traditional-modern. T2 is simplicity-complexity. T3 is ordinary-strange. T4 is compact-atmospheric. T5 is function-decoration. T6 is harmony-contrast. (2) Statistical analysis of data: The average value is obtained by means of analysis and calculation according to the scale data, and the result is shown in Fig. 8.

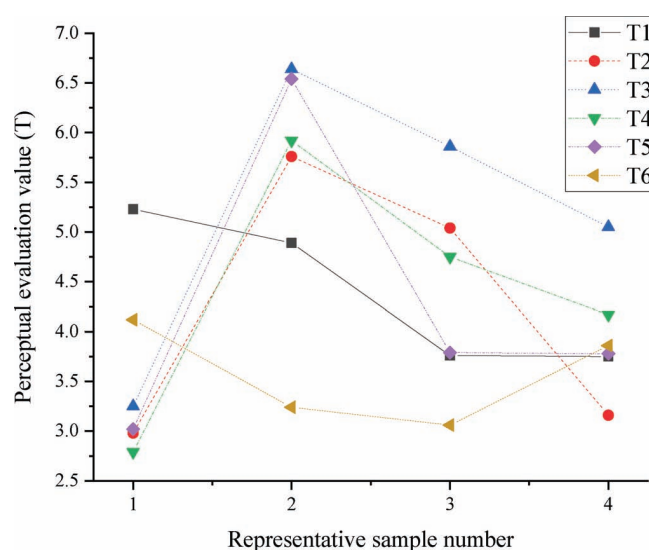


Fig. 8: Representative sample perceptual evaluation value (T).

The perceptual evaluation values of the first group of four representative samples of ceramic products are 5.23, 4.89, 3.76 and 3.75, respectively. The perceptual evaluation values of the second group of descriptive words are 2.98, 5.76, 5.04 and 3.16, respectively. The perceptual evaluation values of the third group of descriptive words are 3.25, 6.64, 5.83 and 5.05, respectively. Different ceramic products have different evaluation values. On the whole, the evaluation value of the first group is higher, which shows that the first group is more popular with people.

The input data for the BP neural network and the value of characteristic elements of ceramic verification samples are used as the input data for the BP neural network prediction model, and the output data of the BP neural network and the value of sample image vocabulary are used as the output data. Because the number of ceramic modeling feature elements and the number of ceramic representative images remain the same, the number of input data and output data of BP neural network prediction model is 14 and 6 respectively. In MATLAB software, taking 6 ~ 18 hidden layers as examples, the number of hidden layers is selected, and 12 hidden layers with the smallest error are selected as the final number of hidden layers. Training neural network with MATLAB. The output data of the BP neural network prediction model are shown in Table 6.

Table 6: The perceptual evaluation of the second network verification sample.

	1	2	3	4
Tradition - Modern	0.7443	0.6905	0.5450	0.5335
Simplicity - Complexity	0.4677	0.8165	0.7042	0.4587
Ordinary - Strange	0.4611	0.9466	0.8230	0.7177
Compact - Atmospheric	0.4633	0.8395	0.6870	0.6015
Function - Decoration	0.4537	0.7652	0.5684	0.6524
Harmony - Contrast	0.5684	0.8542	0.4598	0.6584
Gorgeous - Simple	0.5372	0.4633	0.4427	0.5418
Feminine - Cool and elegant	0.6654	0.5744	0.5547	0.6475
Satisfaction with ceramic modeling	0.7625	0.7505	0.8301	0.6912

According to the data in the table, the satisfaction of ceramic modeling is 0.7625, 0.7505, 0.8301 and 0.6912. The neural network is trained by MATLAB, and the output data of BP neural network prediction model are 0.7625, 0.7501, 0.8300 and 0.6915, which are similar to the satisfaction value of ceramic modeling in the table, so it is considered that the BP neural network prediction model conforms to the prediction accuracy. In this paper, the Kano model and BPNN model are integrated to analyze and predict the design of daily ceramic products. Compared with traditional methods, this comprehensive method can understand consumer demand more comprehensively and predict customer satisfaction. Compared with other studies, this paper obtains different consumer preferences and ranks the importance of different characteristics in a similar way. The BPNN model proposed here is more reliable for predicting customer satisfaction. Compared with other studies in the same field, the data preprocessing and optimization strategy adopted has achieved better results.

V. Conclusions

With the application of daily ceramics in life, people pay more attention to the design of daily ceramics. This paper has made an important exploration and contribution in the field of daily ceramic product design. The innovation of this paper lies in the combination of the Kano model and BPNN models, which are applied to the design of daily ceramic products. This integration method provides researchers with a more comprehensive analysis perspective to better understand the relationship between product design elements, image vocabulary and customer satisfaction. In this way, this paper is committed to improving the design quality of daily ceramic products and meeting the needs of consumers more accurately. This comprehensive method has a certain innovation and practical value for the field of daily ceramic product design. Firstly, through the application of the Kano model, this paper deeply understands the consumer's demand for daily ceramic products. The items that consumers value most in design are found, such as flower patterns, accurate pattern printing and custom pattern selection, as well as relatively low-demand items, such as production technology, pattern layout, and animation pattern style. These findings provide powerful guidance for the future design of dai-

ly ceramic products. On the other hand, the application of BPNN provides a new perspective for predicting customer satisfaction. The optimized model successfully approximates customer satisfaction, indicating that the neural network has considerable forecasting potential in this field. This provides a reliable tool for future product design and marketing, and can better meet customer needs. However, people should also pay attention to the problem that optimizing data preprocessing in BPNN may lead to increased computational complexity. The future research direction should include improving the prediction accuracy and optimizing the calculation efficiency. By simplifying data preprocessing or adopting more effective algorithms, the calculation burden can be reduced, so that it can be better applied to actual product design and market operation. In the future, the development of daily ceramic product design should focus on combining advanced prediction models and consumer insight to achieve more personalized design that meets market demand. With the data-driven method, the matching degree between product characteristics and consumer expectations is continuously optimized to promote product innovation and improvement. Meanwhile, people should pay attention to product manufacturing technology, pattern design and technological innovation to improve product quality and differentiation and meet the changing market demand. Generally speaking, this paper provides important empirical analysis and prediction model support for daily ceramic product design, provides guidance for future research and practice, and encourages further exploration to promote development and innovation in this field.

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Data Availability

All data generated or analysed during this study are included in this published article (and its Supplementary Information files).

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