Fusion of Rough Set Theory, Genetic Algorithm-Backpropagation Neural Networks and Shapley Additive Explanations for the Design of Bamboo Furniture

Zhongchen Huang,[a] and Li Ye [b,*]

In today's competitive market, meeting consumers' satisfaction and emotional needs is crucial for business success. However, the cognitive gap between designers and consumers often hinders market recognition for bamboo furniture. Therefore, a research framework based on Kansei Engineering (KE) is proposed in this study. First, the emotional needs and related samples were collected, and the sample form was deconstructed systematically. Then, the attribute reduction algorithm in rough set theory was used to extract the key emotional needs that have significant impact on consumer satisfaction. Finally, an intelligent mapping model between product components and emotional needs was constructed using Genetic Algorithm-Backpropagation Neural Networks (GA-BPNN), which predicts the optimal product design parameters that meet users' emotional needs. Additionally, we conducted an interpretative analysis of the prediction model using the Shapley Additive Explanations (SHAP) method. The evaluation results were significantly higher than the average, validating the advanced and effective nature of the method proposed in this study. Compared with previous KE studies, the GA-BPNN model proposed in this study has better prediction efficiency and higher precision, which can more effectively solve the cognitive differences between designers and consumers. Thus, the development efficiency and decision-making accuracy of enterprises' product design has been improved.

DOI: 10.15376/biores.20.3.7107-7133

Keywords: Bamboo furniture; Kansei engineering; Rough set theory; Genetic Algorithm-Backpropagation Neural Networks; Shapley Additive Explanations; Bamboo chair

Contact information: a: Department of Space Design, Hoseo University, Asan 31459, Korea; b: Xiangsihu College of Guang Xi Minzu University, Nanning 530000, China;
*First author: 20225215@vision.hoseo.edu; *Corresponding author: 20201411591@stu.gxau.edu.cn*

INTRODUCTION

The origin of bamboo furniture can be traced back to ancient East Asia, especially China and Japan (Deng *et al.* 2023). Because bamboo grows quickly and it is light and tough, early people used this natural material to make furniture (Yuan *et al.* 2022). Over time, bamboo furniture has not only been favored for its unique aesthetics and practicality, but also gradually became a cultural symbol, reflecting the concept of harmonious coexistence between man and nature (Shi *et al.* 2023). In modern society, bamboo furniture with its environmentally friendly nature and sustainable characteristics has once again attracted people’s attention and become an important part of sustainability living (Fan *et al.* 2024).

In the current era of Kansei consumption, consumers’ purchase decisions are not only based on product functions and prices but also on emotional experience and personalized needs (Achar *et al.* 2016; Hu *et al.* 2022). As the differences in function and quality of furniture companies in the market gradually narrow, consumers are more likely to be influenced by design and brand image when faced with numerous choices (Al Hamli and Sobaih 2023). Therefore, furniture designers need to pay more attention to product design so as to meet the needs of users. Consumers can be attracted by the shape of furniture and details that can create emotional resonance and a memorable first impression (Yu *et al.* 2024). Therefore, the importance of Kansei design becomes more prominent. Furniture design is no longer just the presentation of practicality, but enhances users' experiences by conveying emotions, stories, and cultural values (Chen 2022; Zhang *et al.* 2022; Zhou *et al.* 2023a). However, there is a huge cognitive difference between designers and consumers. It is impossible to accurately measure users' needs, resulting in the difference between the final product and the real needs of users. Therefore, designers can cooperate with industry experts through an integrated approach. Designers can convey emotions through language design and incorporate brand stories into products to enhance consumers' identify (Yang *et al.* 2024).

Kansei Engineering (KE) is an interdisciplinary approach that combines the emotional needs of users with product design, which aims to improve the market competitiveness of products by understanding and satisfying the emotional experience of consumers (Nagamachi 1995; Yang *et al.* 2023). As consumers increasingly attach importance to the emotional value of products, KE has been widely applied in such fields as product design (Fu *et al.* 2024), user experience (Liu and Yang 2022), clothing design (Ge *et al.* 2023; Jiang *et al.* 2024) and service innovation (Hartono *et al.* 2024). However, in practical application, KE faces two major challenges. (1) The first challenge is to extract users' emotional needs. At present, researchers usually use quantitative methods such as analytic hierarchy process (AHP) and fuzzy analytic hierarchy process (FAHP) to obtain users' emotional feedback. Ramanathan *et al.* (2023) extracted the necessary design elements of the convenient skimmer by using KE; the optimal design scheme is selected by using AHP method. Wang *et al.* (2024) proposed an AI-driven design method which combines shape grammar and KE. In this process, the hierarchical structure model of grey analysis is used to extract the optimal Kansei words. Qi and Kim (2024) adopted AHP to effectively combine objective criteria and subjective users' perception to establish the relationship between design features and emotional needs and establish an evaluation system of design images. Lin and Zheng (2024) used F_AHP to extract the optimal Kansei needs of AR dashboard's visual images; FRA is further used to extract the optimal AR dashboard design. The above methods, although structurally rigorous, have a high computational complexity when dealing with multidimensional and multilevel data. In contrast, Rough Set Theory (RST) provides an effective tool for data analysis that can extract meaningful knowledge from incomplete or uncertain information without relying on precise attribute values to better capture the emotional needs of users (Pawlak 1998; Thangavel and Pethalakshmi 2009; Zhang *et al.* 2016). This method is especially suitable for dealing with complex emotional needs, because the emotions of consumers are often difficult to accurately describe by traditional quantitative indicators, while the RST can reduce the requirement for accuracy while retaining important information (Sato *et al.* 2022). Li (2024) used RST to extract products' Kansei needs that has a significant impact on customers' satisfaction and used it to analyze products' Kansei knowledge. Chen (2024b) used the RST attribute reduction algorithm to identify the form characteristics of low-speed new energy vehicles that are most concern to elderly users. Kang (2021) used the RST attribute reduction algorithm to extract the new energy vehicle design elements that have an important impact on consumers' satisfaction. Akgul *et al.* (2020) explored the basic elements of new customer-oriented baby bassinet based on the KE method of RST. Chen (2024a) took the human-machine interaction interface of autonomous vehicles as the research object to identify HIM interface elements that have a greater impact on elderly users. In the field of KE, many researchers have begun to focus on how to use RST to establish a relationship with consumers' emotional needs, but there is still a problem of insufficient depth and breadth of application of RST. Therefore, this study aims to further explore the application of RST attribute reduction algorithm in extracting the optimal emotional needs of consumers; a more systematic and comprehensive model is built in order to more accurately capture consumers' innermost emotional expectations.

The second challenge of KE is to establish a mapping relationship between products and emotions (Kang 2024). At present, many researchers use traditional quality function deployment (QFD) (Ginting *et al.* 2020), fuzzy QFD (Fu *et al.* 2024) quantitative type 1, multiple linear regression, Kano (Cai *et al.* 2023) and other methods to establish the mapping relationship between users' requirements and design parameters. Fu *et al.* (2024) combined F-AHP and fuzzy QFD to develop new mahogany furniture that is in line with users' emotions; fuzzy QFD is used to establish the relationship between consumers' needs and engineering characteristics; and then the priority of mahogany furniture design elements is determined. Wang and Yang (2023) applied GRA, QFD and other models to the design of wicker development. GRA is used to extract key emotional needs. QFD is used to build a transformation model between emotional needs and design parameters; the optimal design parameter is derived. Li *et al*. (2024) aimed to determine the needs of elderly users for home glucose meters; QFD is used to determine the relationship between specific product functions and service design elements after determining the priority of demands. Although the above methods are effective, they are often insufficient in dealing with complex nonlinear relationships. These methods are prone to over fitting when faced with a large number of variables and interaction effects (Wang *et al.* 2024).

In contrast, Backpropagation neural network (BPNN) can capture complex nonlinear relationships with self-adaption through learning a large number of data samples, thereby improving mapping accuracy (Al-Jarrah *et al.* 2022; Lin *et al.* 2023). In order to explore multi-sensory design of products, Li *et al.* (2023) took electric shaver as the research object and used BPNN and GA-BPNN to establish a predictive model between design elements and users' Kansei evaluation. Zhao *et al.* (2024) used Whale to optimize BPNN and SVR algorithms to build the relationship between product shape and consumer emotion; whiskey bottle was taken as the research object to predict the optimal design and discuss the accuracy of the nonlinear model. Zimo *et al*. (2024) used BPNN to establish the nonlinear functional relationship between the morphological characteristics of the new energy vehicles' front face and the emotional needs of consumers, and the optimal design combination of new energy vehicles' front face was predicted. Although BPNN has become an important tool in affective design, it must be acknowledged that BPNN suffers from the disadvantages of data overfitting phenomenon and long training time. At the same time, genetic algorithm, as an optimization technology, can be combined with neural network to optimize the network structure and parameters through evolutionary algorithm, thus the model performance can be improved (Wu *et al.* 2023). GA-BPNN has been effectively applied in engineering, financial projects and other fields. Sun *et al*. (2025) used GA-BPNN and PSO-BPNN to predict the flammability of hot thick solids. Liang *et al.* (2022) used GA-BPNN to make a comparative analysis of tunnel parameters to find the cause of surface instability. Bai *et al*. (2023) established a project portfolio risk assessment model by using GA-BPNN and PAC so as to provide managers with quantitative risk analysis tools. However, there are still few studies on the combination of GA and BPNN in the field of product design at present. Therefore, this study aims to establish a parametric design and evaluation model between consumers' emotional needs and product characteristics by using GA-BPNN. At the same time, since machine learning is often considered a "black-box model," meaning that its internal decision-making process is difficult to understand, we propose applying Shapley Additive Explanations (SHAP) to the GA-BPNN. This approach helps analyze how the model's output is influenced by various design features (input variables), thereby providing interpretability for the model. For GA-BPNN, SHAP offers a method to quantify the specific contribution of each input feature to the model's predictions. This enables us to identify which features have the most significant impact on the decision-making process, offering valuable insights for model optimization.

To sum up, although KE has made some progress in theory and practice, it still faces many challenges in extracting users' emotional needs and establishing mapping relationships. Under the research framework of KE, an improved model combining RST, GA-BPNN and SHAP is proposed in this study. The main contributions of this research are summarized as follows: (1) in the traditional KE research, few scholars use RST to extract the key Kansei needs of consumers in the Kansei intention analysis stage, (2) GA-BPNN method establishes the mapping relationship between product parameters and emotional needs, which predicts the optimal scheme and improves the prediction performance of the traditional model. (3) The inclusion of SHAP-based interpretability analysis in GA-BPNN can help designers and data scientists understand the model's behavior, promote its optimization, and improve compliance. By assigning a "contribution value" to each feature, it provides a transparent decision-making process, making the complex GA-BPNN model more interpretable, reliable, and usable. (4) The model proposed in this study can enable designers to grasp the emotional needs of consumers in real time and narrow the cognitive gap between designers and consumers. From the perspective of consumers, it can improve consumers' purchase intention for this type of product. From the perspective of enterprises, it can increase product sales and improve the market competitiveness of enterprises.

RELATED METHODS

This research is divided into four stages, as shown in Fig. 1. (1) Users' emotional needs are collected under the research framework of KE, and KJ method is used for initial clustering. The morphology deconstruction method is used for bamboo furniture. (2) The attribute reduction algorithm of RST is used to extract the optimal emotional needs. (3) GA-BPNN is used to build a parametric design system between key emotional needs and product parameters. (4) The SHAP framework is used to analyze the contribution of design parameters. By employing a parametric design system, the optimal design solution is determined. Product design is then carried out, and the feasibility of the method is verified through user evaluations.

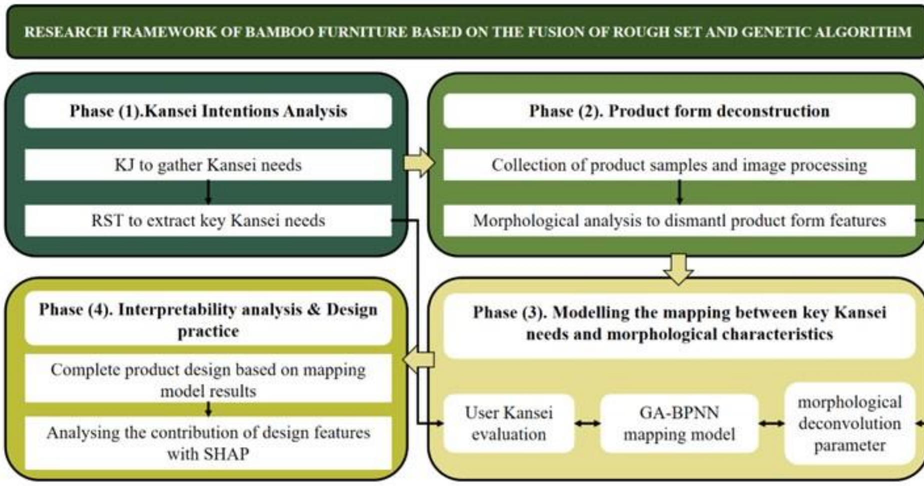

Fig. 1. Bamboo furniture sensory design research framework

Rough Set Theory

RST can analyze data on the basis of given inherent information without any auxiliary information or subjective judgment. Its knowledge expression system is represented by 4-tuple, namely $S = (U, A, V, f)$. As one of the main functions of RST, attribute reduction is the minimum conditional attribute set which does not contain redundant attributes and guarantees the correct classification. The intersection of these reductions is defined as the *core* of decision table; and the attributes of the *core* are important attributes that affect the classification. The relevant definitions are as follows:

Definition 1: suppose in the decision table D and for any C_j; if C_j satisfies the formula:

$$POS_{ind(C)}\big(ind(D)\big) = POS_{ind(C-\{C_j\})}\big(\mathrm{ind}(D)\big) \tag{1}$$

C_j is called to be unnecessary for D in C; Otherwise, C_j is necessary for D in C; The set of all necessary primitive relations in C is called the D core of in C, which is denoted as $\mathrm{core}_D(C)$.

Since the importance of each attribute in the information knowledge base is not the same, it is necessary to focus on the attributes of higher importance. The importance of attributes is defined as follows:

Definition 2: the dependence of decision attribute D on the conditional attribute C_j is defined as

$$\gamma c_j(D) = \frac{card\Big(pos_{c_j}(D)\Big)}{card(U)} \tag{2}$$

In this formula, $\gamma c_j(D)$ is the dependence between the decision set D and the attribute C_j; card is the base of the corresponding set.

$$\gamma_C(D) - \gamma_{(C-C_j)}(D) = \frac{card(pos_c(D)) - card\Big(pos_{(C-C_j)}(D)\Big)}{card(U)} \tag{3}$$

when C_j is removed from C, the value of $\gamma c_j(D)$ will be changed to measure the importance of the attribute C_j.

Genetic Algorithm-Backpropagation Neural Network

Backpropagation neural network

Backpropagation neural network is a simple gradient descent algorithm for supervising learning, which consists of an input layer, an output layer and one or more hidden layers. At the same time, BPNN has the advantages of self-learning, self-organization, better fault tolerance and excellent nonlinear approximation ability. The following is a brief description of the implementation steps of BPNN:

(1) Network structure design: the number of network layers and the number of neurons in each layer are determined, which usually includes input layer, hidden layer and output layer. Set $\mathrm{n_i}$ as the input layer; $\mathrm{n_h}$ is set as the hidden layer and $\mathrm{n_o}$ is set as the output layer.

(2) Initialize weights and bias: the weight $\mathrm{w_{ij}}$ and the bias $\mathrm{b_j}$ between the connected layers are randomly initialized. These parameters are constantly updated during training.

(3) Forward propagation: the input data is propagated forward through the network to calculate the output of neurons in each layer. As for the neuron of No. n layer, the output can be expressed as:

$$\mathrm{a}_{\mathrm{j}}^{(n)} = \mathrm{f}\left(\sum\nolimits_{\mathrm{i}} \mathrm{w}_{\mathrm{ij}}^{(n-1)}\mathrm{a}_{\mathrm{i}}^{(n-1)} + \mathrm{b}_{\mathrm{j}}^{(n)}\right) \tag{4}$$

(4) Error calculation: the error is calculated at the output layer, namely the difference between the actual output and the expected output. It is commonly measured by mean square error (MSE).

$$MSE = \frac{1}{\mathrm{M}}\sum\nolimits_{\mathrm{k=1}}^{\mathrm{M}} (\mathrm{y_k} - \hat{y}_{\mathrm{k}})^2 \tag{5}$$

(5) Backpropagation: the gradient of each layer's weight and bias is calculated according to the chain rule. These parameters are updated to reduce error. At layer n, the weigh update formula is as follows:

$$\mathrm{w}_{\mathrm{ij}}^{(n)} = \mathrm{w}_{\mathrm{ij}}^{(n)} - \eta\frac{\partial \mathrm{E}}{\partial \mathrm{w}_{\mathrm{ij}}^{(n)}} \tag{6}$$

(6) Iterative training; the forward propagation, error calculation and Backpropagation steps are repeated until a predetermined stop condition is reached, such as a maximum number of iterations or error less than a certain threshold.

Genetic algorithm

Genetic Algorithm (GA) is an optimization algorithm based on the principles of natural selection and genetics, which aims to find the optimal solution by simulating the biological evolution process (Scrucca 2013). It evaluates each coding individual through a self-defined fitness function; and it removes the bad individual, selects the adaptive coding individual for selection, crossover and mutation. It also generates the post-generation group several times until the coding individual approaches the optimal solution. In this paper, GA-BPNN combines the advantages of both GA and BPNN and optimizes the weight and bias in BPNN through GA to improve the model performance. In GA-BPNN, GA is used to search for the best weight configuration, while BPNN is used to establish complex data mapping relationships (Fu *et al.* 2023). This combination makes the model not only have high accuracy but also can effectively avoid the problem of local optimal solution and improve the overall optimization effect. The flow chart of GA-BPNN is shown in Fig. 2 and the steps are as follows:

(1) Initial population: at the beginning of GA, an initial population is randomly generated, with each individual (chromosome) representing a possible solution. Each individual consists of a set of parameters, which are usually variables for the problem to be optimized.

$$\text{Individual} = [x_1, x_2, \ldots, x_n] \tag{7}$$

(2) Fitness assessment: for each individual, a fitness value is calculated based on its performance in the objective function. For example, as for the minimization problem, fitness can be defined as:

$$\text{Fitness} = \frac{1}{1+f(x)} \tag{8}$$

(3) Selection and crossover: select individuals for breeding based on fitness value. The common selection methods include roulette selection, tournament selection, which aims at preserving excellent genes and generating the next generation. Crossover is the process of combining two parent individuals to produce a new individual. The common crossover methods include single-point crossover and multi-point crossover. For example, in a single point crossover, a crossover point can be randomly selected to exchange the genes of the parent:

$$C_1 = \left[P_{1,1}, P_{1,2}, \ldots, P_{1,k}, P_{2,k+1}, \ldots, P_{2,n}\right] \tag{9}$$

(4) Mutation operation: mutation is the random change of certain genes in the newly generated offspring to increase the diversity of the population. Mutation can be achieved by simply and randomly adjusting certain parameters. For example, mutation can be represented by the following formula:

$$C_j = C_j + N(0, \sigma) \tag{10}$$

(5) Stop condition: the newly generated next generation is combined with the original population; and the next generation population is selected according to the fitness; the elite strategy is usually adopted to retain several individuals with the highest fitness. Determine if the stop condition is met, such as reaching the maximum number of iterations or no significant improvement in fitness. If the condition is met, the current optimal individual is output as the optimization result.

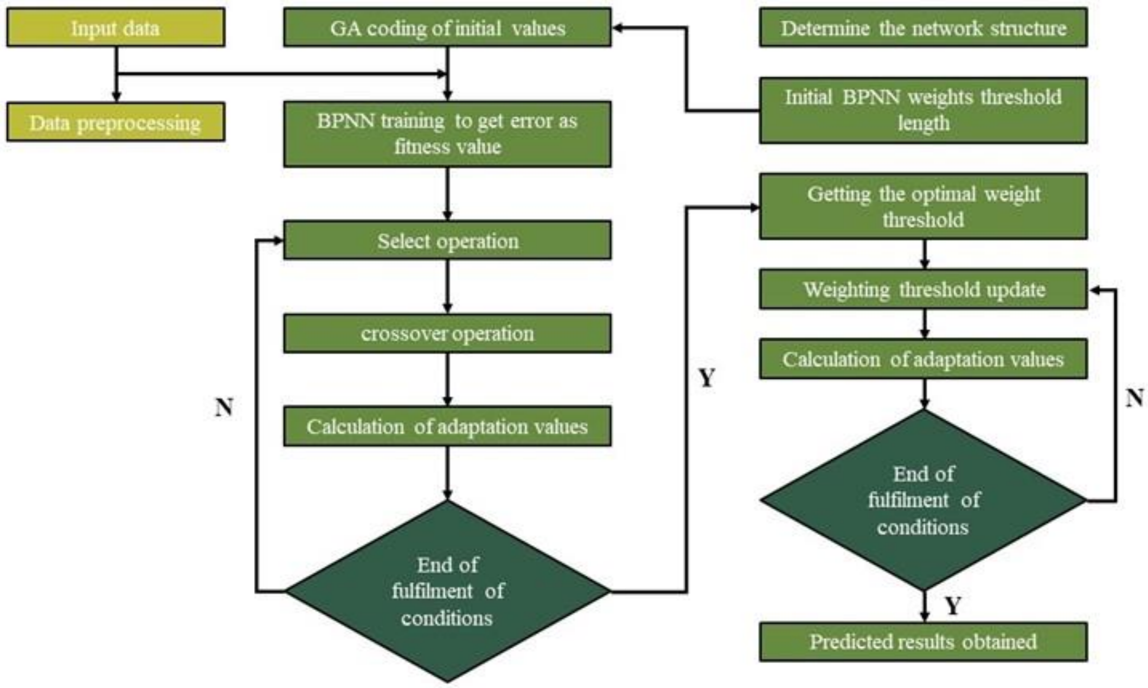

Fig. 2. Operational process of the GA-BPNN model

Shapley Additive Explanations

The SHAP method estimates the impact of a feature by observing the model's behavior with and without that feature. To achieve this, the feature attribution problem is transformed into a cooperative game theory problem. The SHAP value is the unique, consistent, and local precise solution that calculates the contribution of each feature to the final output when an attribute is missing (with the missing feature's attribution set to zero). The SHAP value provides a numerical measure that indicates the average contribution of a feature to the model's prediction, considering all possible combinations of the other features. A positive value indicates that the feature has a positive impact on the prediction, while a negative value indicates a negative contribution. The Shapley value for a feature *i* in a feature set S is calculated as follows:

$$\emptyset_i = \sum_{S \in N} \frac{|S|!(|N|-|S|-1)!}{|N!|}(v(S \cup \{i\}) - v(S)) \tag{11}$$

When applying the SHAP framework, the first step is to train a machine learning model to predict user sentiment in furniture design. Then, SHAP is used to analyze the impact of each design feature on the user sentiment outcome. By examining the marginal contribution of each feature to the prediction, we can identify which features play a key role in predicting user sentiment in the design task. Specifically, SHAP represents the model's prediction *f(x)* as the sum of contributions from each feature, as shown in Formula (12).

$$f_{(x)} = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i \tag{12}$$

RESEARCH PROCESS AND RESULTS

The bamboo chair in the bamboo furniture is taken as the research object in this study; and the feasibility of the proposed research framework is verified. As a unique form of furniture, the bamboo chair not only reflects the excellent characteristics of bamboo, such as light weight, strong, and environmentally friendly, but also integrates traditional crafts and modern design concepts, which has become a popular choice in the contemporary home environment. With the increasing attention to sustainable lifestyle, the market demand for bamboo chairs has also risen, especially in the pursuit of nature and environmental protection under the consumption trend. The bamboo chair shows broad prospects for development. In China, as a country with a long history of bamboo culture and rich furniture tradition, consumers pay attention to its practicality and comfort and to its cultural connotation and artistic value. In the product development process, the cultural background of consumers has a profound impact on their needs and preferences. Therefore, this study focuses on the analysis of Chinese consumers' cognition and preference for bamboo chairs so as to provide more targeted suggestions and guidance for the development of bamboo furniture. Consumers in different regions and different cultural backgrounds have significant differences in the function, aesthetics, and usage habits of furniture. Therefore, when new product development is conducted, it is necessary to re-investigate the needs of local consumers to ensure that the product can truly meet the expectations of the target market.

Preliminary Preparation for Perception Experiment

Collect and cluster Kansei words through KJ and PAD model

In this study, through relevant literature, websites and books, 24 Kansei words about the bamboo chair are initially collected. These words are designed to capture consumers' emotional and cognitive responses to bamboo chairs. However, too many Kansei words may increase the cognitive load of the participants, thus the quality of the questionnaire data will be reduced. In order to solve this problem, a group of five furniture design experts and five design graduate students were formed. KJ is an effective information organizing tool. By grouping and categorizing related words, the expert group can identify the most representative and influential Kansei words, thus simplifying the follow-up questionnaire design. In this study, KJ method was used to reorganize and classify the collected Kansei words, and cluster the Kansei words according to the principle of similarity (Fig. 3). Eight representative Kansei words were obtained: simple, creative, soft, flexible, tough, elegant, traditional, and ancient.

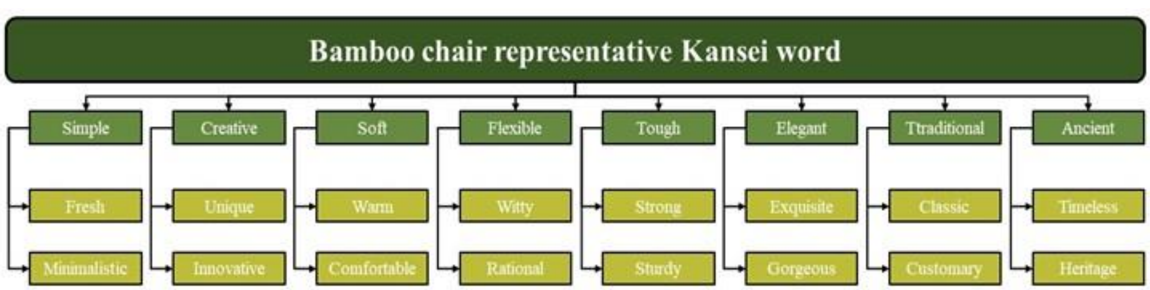

Fig. 3. Bamboo chair representative Kansei word

To enhance the objectivity of clustering results, this study introduces the Pleasure-Arousal-Dominance (PAD) emotional model to quantitatively calibrate the perceptual dimensions derived from the KJ method. By mapping each perceptual dimension onto a three-dimensional emotional space (pleasure, arousal, dominance), the emotional response mechanisms of users toward design features can be systematically interpreted. The PAD ratings in this study were determined through expert panel evaluations. The panel assessed the emotional intensity of sub-vocabulary items on a 1-9 scale, with consistency ensured *via* Kendall's coefficient of concordance (W=0.82). Additionally, culturally sensitive terms were adjusted with reference to Mehrabian's standardized PAD vocabulary database. Table 1 presents the PAD scores and explanatory logic for each dimension and its sub-vocabulary. Quantitative validation of the clustering results using the PAD model revealed significant emotional consistency within dimensions and clear emotional distinctions between them. Specifically, sub-vocabulary items under the same perceptual dimension exhibited highly convergent patterns in the PAD space. For instance, "Warm" and "Comfortable" in the "Soft" dimension both demonstrated extremely high pleasure (P=9) and very low arousal (A=2), with a standard deviation (SD) below 0.5. Conversely, "Strong" and "Sturdy" in the "Tough" dimension shared high arousal (A=7) and high dominance (D=8), with all dimensions showing a coefficient of variation (CV) below 15% for PAD scores. Meanwhile, significant differences were observed between dimensions in the emotional space, particularly in arousal levels. For example, the arousal intensity of the "Creative" dimension (A=8) was four times that of the "Ancient" dimension (A=2). Multivariate analysis of variance (MANOVA) confirmed significant overall PAD differences between dimensions (Wilks' λ=0.12, $p<0.001$), with arousal showing the most pronounced inter-group variance (F=37.52, $p<0.0001$). Discriminant analysis further indicated a 92% correct classification rate for vocabulary across dimensions, with a 100% distinction between "Creative" and traditional dimensions. The PAD model validated the intrinsic rationality of clustering through emotional quantification. These results demonstrate that the clustering outcomes of this study not only align with semantic logic but are also interpretable at the level of emotional response.

Table 1. PAD Scoring and Interpretation of Perceptual Vocabulary Clusters

Emotional Dimension	Sub-vocabulary	P	A	D	Interpretation Logic
Simple	Fresh, Minimalistic	7	3	5	High pleasure (comfort from simplicity), low arousal (non-stimulating), medium dominance (easy to control)
Creative	Unique, Innovative	8	8	4	High pleasure (excitement from innovation), high arousal (stimulates curiosity), low dominance (uncertainty)
Soft	Warm, Comfortable	9	2	6	Extremely high pleasure (warm comfort), very low arousal (relaxation), medium-high dominance (environmental controllability)
Flexible	Witty, Rational	6	5	7	Moderate pleasure (clever rationality), moderate arousal (requires thought), high dominance (logical control)
Tough	Strong, Sturdy	5	7	8	Moderate-low pleasure (potential oppression), high arousal (power stimulation), high dominance (stability provides security)
Elegant	Exquisite, Gorgeous	8	4	6	High pleasure (refined beauty), moderate-low arousal (calm elegance), medium dominance

					(appreciation without ownership)
Traditional	Classic, Customary	6	3	7	Moderate pleasure (familiarity), low arousal (conventional), high dominance (clear rules)
Ancient	Timeless, Heritage	7	2	5	High pleasure (timeless value), very low arousal (nostalgic tranquility), medium dominance (historical weight)

Collection of representative samples of bamboo chairs

This study aimed to ensure that the research samples included different styles, functions, and design concepts of bamboo chairs, and ensure that the diversity of bamboo chairs in the market was fully reflected. In this study, a total of 120 bamboo chair samples were collected through various channels, including furniture exhibitions, design fairs, furniture stores and online platforms. The expert group focused on eliminating samples with excessive repeatability and chaotic background, which resulted in 50 representative samples that were retained. The design team used Photoshop to remove the background of samples, and the bamboo chair database of this study was formed, as shown in Fig. 4.

Fig. 4. Bamboo chair sample database

Morphological deconstruction table of bamboo chairs is construed through the morphological analysis

Morphological analysis was used to analyze and deconstruct the design features of bamboo chairs, which aims at establishing the relationship between users and products when the mapping models are constructed (Wang *et al.* 2024). Morphological analysis is a systematic analysis tool that helps researchers understand the structure, function and aesthetic characteristics of a product by breaking down its various components. In this process, the expert group first observed the overall shape of the bamboo chairs and identified its main components, including the back of the chair, the seat surface, the armrest, the legs and the way of bamboo-weaving. Each design component element was subdivided again as an independent variable, and finally the morphological deconstruction table of the bamboo chairs was established (Fig. 5).

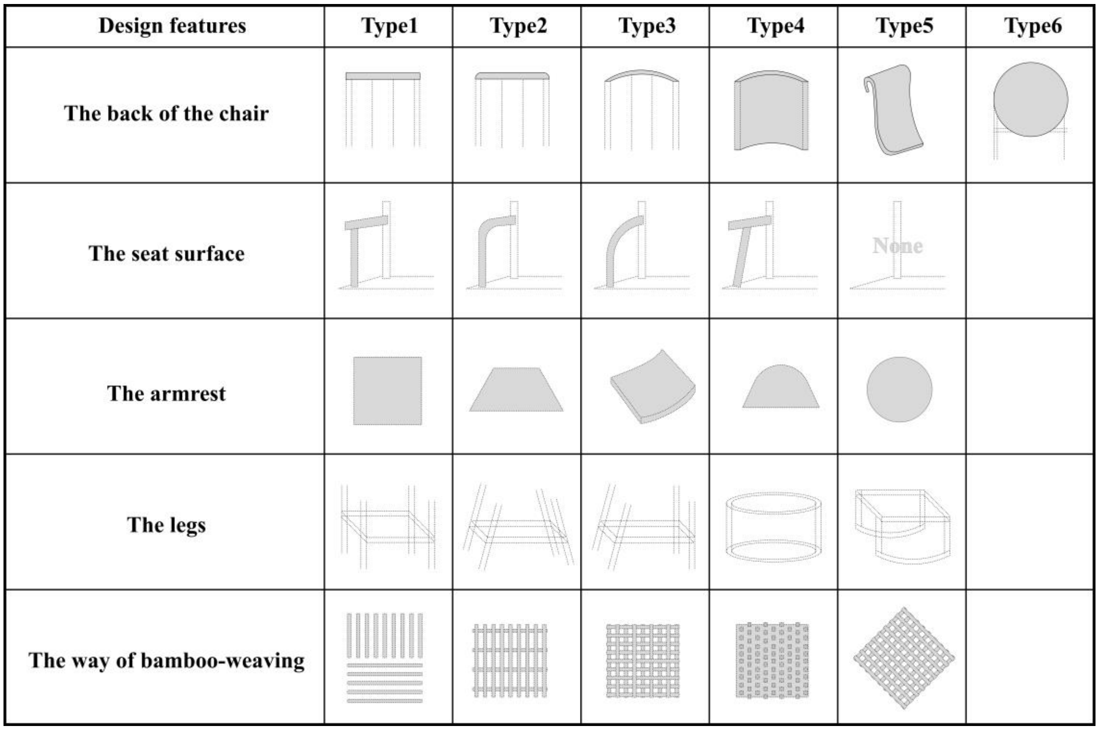

Fig. 5. Operational process of the GA-BPNN model

Extract the Optimal Emotional Needs of Users

Perception experiment of users on bamboo chairs

In the stage of users' perception experiment on bamboo chairs, 7-step Likert scale was used in this study to conduct perception experiment on users. Firstly, the questionnaire of perception evaluation and satisfaction evaluation was made. The content of the questionnaire covered the user perception evaluation and satisfaction rating of 50 representative samples to comprehensively understand the consumers' emotional response and user experience of bamboo chairs. A total of 150 Chinese consumers were invited to participate in the questionnaire survey, with 8 invalid responses excluded, resulting in 142 valid questionnaires retained for analysis. Table 1 summarizes the demographic characteristics of respondents, including gender distribution (52.1% female, 47.9% male), age groups (18-25: 38.7%, 26-35: 41.5%, 36-45: 19.8%), geographic regions (First-tier cities: 63.4%, Central/Western China: 36.6%), and occupational categories (students: 28.2%, professionals: 44.4%, others: 27.4%). The mean values of questionnaire responses were calculated to construct the users' perception and satisfaction evaluation matrix, as shown in Table 1.

A comprehensive survey of 142 Chinese consumers was conducted to explore their emotional needs and perceptions in seating design. The stratified analysis reveals systematic variations in Kansei responses across demographic cohorts. The analysis revealed systematic variations in Kansei (aesthetic and emotional response) across different demographic cohorts. Gender differences highlighted distinct preferences: females showed stronger evaluations for "Soft," while males emphasized "Tough." Students and professionals exhibited differentiated preferences, with students valuing "Creative" and " Flexible," and professionals favoring "Elegant" and " Traditional." Manual workers' unique association with "Ancient" materials suggests a cultural and emotional connection to traditional craftsmanship. Additionally, urban hierarchy contrasts revealed modernization gradients, with first-tier city residents showing stronger connections between "Creative" and "Elegant," aligning with globalized design trends, while second-tier residents preserved "Traditional" and "Ancient" aesthetics. The above research has identified heterogeneity in the emotional needs of different groups, so there is a need to continue to gain insight and extract key emotional needs based on the above to inform the design process and close the gap between consumer expectations and product design.

The optimal emotional needs of users extracted by rough set theory

By identifying the emotional needs that have a significant impact on users' satisfaction, the emotional factors that do not have a significant impact on users' satisfaction can be effectively reduced. This process not only simplifies the complexity of data analysis but also improves the efficiency and accuracy of the model. In actual operation, SPSS software was used in this study to process the data in Table 2 by binning process. The first interval was defined as discrete value 1; the second interval was defined as the discrete value 2 and the third interval was defined as the discrete value 3. The binning processing interval is shown in Table 3. A decision table containing 8 kinds of emotional needs and satisfaction was established, in which the Kansei needs are conditional attributes, and the users' satisfaction is the decision attribute, as shown in Table 4.

Table 2. The Users' Perception and Satisfaction Evaluation Matrix

No.	Simple	Creative	Soft	Flexible	Tough	Elegant	Traditional	Ancient	Satisfaction
1	3.225	3.713	3.960	4.120	4.040	4.160	3.213	3.140	4.040
2	3.688	3.150	3.680	4.080	4.160	3.640	3.163	3.650	4.040
3	3.750	3.738	4.240	4.280	3.840	3.800	3.788	3.460	4.400
……	……	……	……	……	……	……	……	……	
48	3.050	3.800	4.000	4.200	4.160	4.000	3.213	3.710	3.760
49	3.013	3.675	4.040	4.640	4.520	4.240	3.125	3.750	4.160
50	3.213	3.225	4.400	4.400	4.280	4.440	3.763	3.720	4.080

Table 3. Data Interval Separation

First interval	3.0125-3.28	3.1-3.45	3.52-3.97	3.4-3.86	3.48-3.96	3.24-3.68	3.125-3.36	3.02-3.64	3.24-3.90
Second interval	3.28-3.55	3.45-3.80	3.97-4.42	3.86-4.33	3.96-4.44	3.68-4.12	3.36-3.6	3.64-4.26	3.9-4.57
Third interval	3.55-3.825	3.80-4.16	4.42-4.88	4.33-4.8	4.44-4.92	4.12-4.56	3.6-3.83	4.26-4.88	4.57-5.24

Table 4. Rough Set Theory Decision Attribute Matrix

No.	Simple	Creative	Soft	Flexible	Tough	Elegant	Traditional	Ancient	Satisfaction
1	1	2	1	2	2	3	1	1	2
2	3	1	1	2	2	1	1	1	2
3	3	2	2	2	1	2	3	3	2
……	……	……	……	……	……	……	……	……	……
48	1	2	2	2	2	2	1	1	1
49	1	2	2	3	3	3	1	1	2
50	1	1	2	3	2	3	3	3	2

Table 5. Weighting of Perceptual Needs

Kansei words	Weight	Kansei words	Weight
Simple	0	Creative	0
Soft	0.105263157894737	Flexible	0.157894736842105
Tough	0.368421052631579	Elegant	0.368421052631579
Traditional	0	Ancient	0

On this basis, the software platform MATLAB 2022Rb was used in this study to screen out the Kansei needs that have an important impact on users' satisfaction through the attribute reduction algorithm of RST. The weight value of each emotional demand is shown in Table 5. Through the comprehensive consideration of expert group, the emotional needs that have an impact on consumers' satisfaction were retained, namely soft, elegant, tough and flexible. This process helps this study focus on key emotional needs, thereby eliminating redundant information and providing clearer and more precise input for subsequent data modeling and algorithm development.

The Mapping Models Between Key Kansei Needs and Design Elements are Built by GA-BPNN

Based on the previous research, the mapping model between the Kansei needs of key users and the key design components was constructed so that it can complete the learning and prediction tasks. Firstly, 50 representative samples of bamboo chairs were disassembled into a combination of design components. Secondly, all samples were unified into 100px square png images. Since the above perception questionnaire covers 8 emotional needs, excessive emotional needs may affect the data results of key emotional factors. So, at this stage, the authors re-collected users' feedback on the key emotional needs of bamboo chairs, and 150 participants were invited to participate in the perception experiment by using the 7-step Likert scale. Participants rated each emotional needs according to their own experience in order to more accurately reflect their emotional cognition and preferences for bamboo chairs. For the corresponding explanation of the questionnaire tasks provided by the subjects, "tough" represents the robustness and durability of bamboo chairs, which reflects its high-quality materials and processes. Therefore, it can withstand greater pressure and abrasion during use. "Elegant" reflects the design beauty and artistic atmosphere of the bamboo chair, which reflects its exquisite and elegant appearance and can enhance the taste of the overall home environment. "Flexible" represents the lightness and flexibility of the bamboo chair, which makes it easy to move and adjust and can adapt to different use scenarios and needs. Thus the convenience and comfort will be brought to users. "Soft" represents the gentle and comfort characteristics of bamboo chairs, which reflects the smooth lines and affinity of its design. It also reflects the choice of natural colors, which makes the bamboo chair be more easily integrated into the home environment. Thus a peaceful and harmonious atmosphere will be created and the users' comfort will be enhanced. Finally, 143 valid data were retained; the statistical analysis of the results' mean value was carried out; the database is provided for the subsequent establishment of the mapping model, as shown in Table 6.

Table 6. Perceptual Mapping Model Matrix

No.	Design Components					Key Kansei Needs			
	The back of the chair (X1)	The seat surface (X2)	The armrest (X3)	The legs (X4)	The way of bamboo-weaving (X5)	Soft	Flexible	Tough	Elegant
1	1	5	1	1	1	3.110	2.970	3.040	3.440
2	2	1	1	1	1	3.080	3.420	3.450	3.430
3	3	1	1	1	1	3.280	3.630	3.810	3.260
……	……	……	……	……	……	……	……	……	……
48	4	3	3	3	2	3.500	3.510	3.880	3.480
49	4	1	1	3	3	3.200	4.920	3.510	3.610
50	1	5	1	3	1	3.150	2.340	2.860	3.690

The attribute coding of five design components was used as the input layer; and the mean attribute of key emotional needs evaluation was used as the output layer. The Kansei mapping model of GA-BPNN was modeled under MATLAB2022Rb software platform. The genetic algorithm was used to optimize the Backpropagation neural network. The set GA parameters include population size of 50, iteration number of 50, crossover probability of 0.8, mutation probability of 0.05, learning rate of 0.01; the fitness function uses the root-mean-square error (RMSE). The number of nodes in the input layer of the BPNN model was determined to be 5 according to the number of features; the number of nodes in the output layer was 4 according to the key emotional needs; the number of nodes in the hidden layer was set to the value between the number of nodes in the input layer and the number of nodes in the output layer. In the course of training, the weight is updated by means of mean square error or cross entropy loss function through Backpropagation algorithm to improve the performance of the model. 90% of the samples are set as the training set and the remaining 10% are set as the test set. After multiple training, the four Kansei mapping models all converge to a good parameter model; the parameter results of the training set show that R^2 is greater than 0.9 and the RMSE is less than 0.2. The parameter results indicate that the model trained in this study has good prediction performance and high fitting degree. Finally, the test set is used to test the model; and the results of the test set parameters show that R^2 is greater than 0.88 and RMSE is less than 0.21. The results show that the prediction results of the model in this study have little difference from the real value; and it can be used for the subsequent design combination prediction research, which is in line with the experimental expectations. In summary, the experimental results of this study show that the constructed GA-BPNN Kansei mapping model has good predictive performance and can be used to establish the mapping relationship between the components of bamboo chair design and Kansei needs. The parameters of the Kansei mapping model are shown in Table 7. The model fitness change curves, test set and training set fitting curves are shown in Fig. 6.

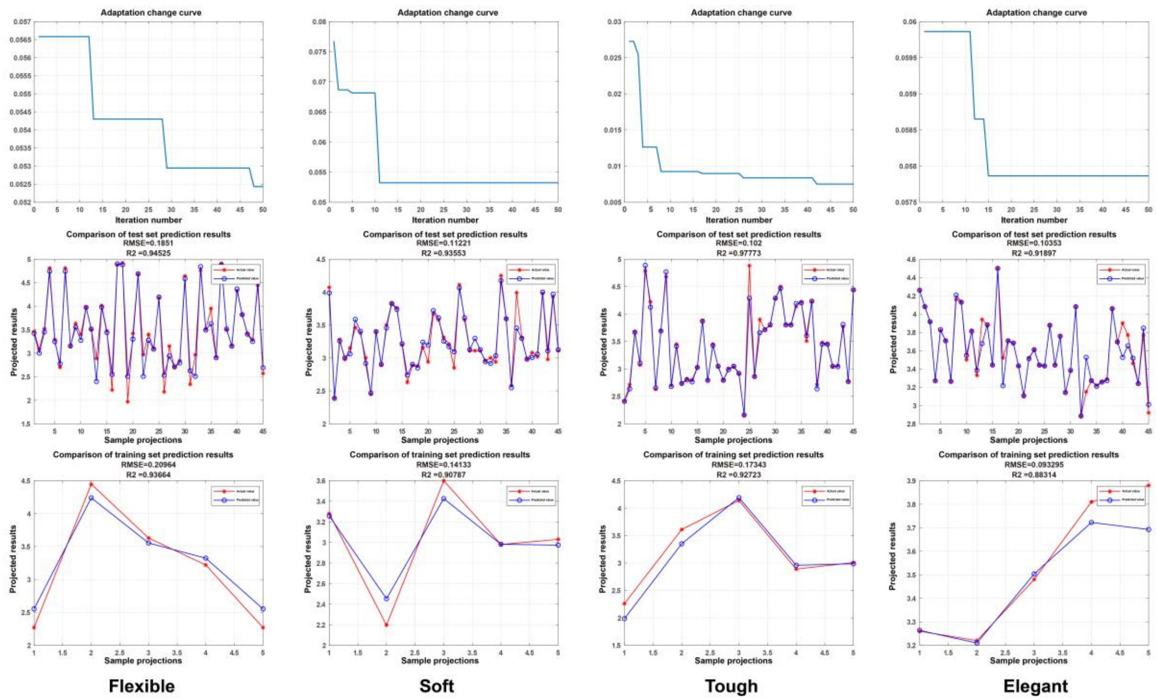

Fig. 6. GA-BPNN test set and training set data fitting plots

Table 7. The Parameters of the Kansei Mapping Model

Kansei needs	Test set fitting data		Training set fitting data	
	R^2	RMSE	R^2	RMSE
Flexible	0.94525	0.1851	0.93664	0.20964
Soft	0.93553	0.11221	0.90787	0.14133
Tough	0.97773	0.102	0.92723	0.17343
Elegant	0.91897	0.10353	0.88314	0.093295

In addition, we have incorporated the SHAP framework into the GA-BPNN algorithm to analyze the contribution of design features to different user emotions. The contribution of each feature to user emotions is calculated, highlighting which design features have a significant impact on user emotions and which have a smaller effect. First, a bee swarm plot was used (Fig. 7) to visualize the influence of five design features on four types of user emotions. Each point in the bee swarm plot represents the SHAP value of a specific feature for a given sample. These points are arranged along the horizontal axis according to the SHAP value of the feature (*i.e.,* the contribution of the feature to the prediction result), while the vertical position (*i.e.,* the position along the vertical axis) helps display the distribution of different features. Additionally, a bar chart was used to show the average impact of the design features, representing the overall contribution of different design features to user emotion prediction results, as shown in Fig. 8.

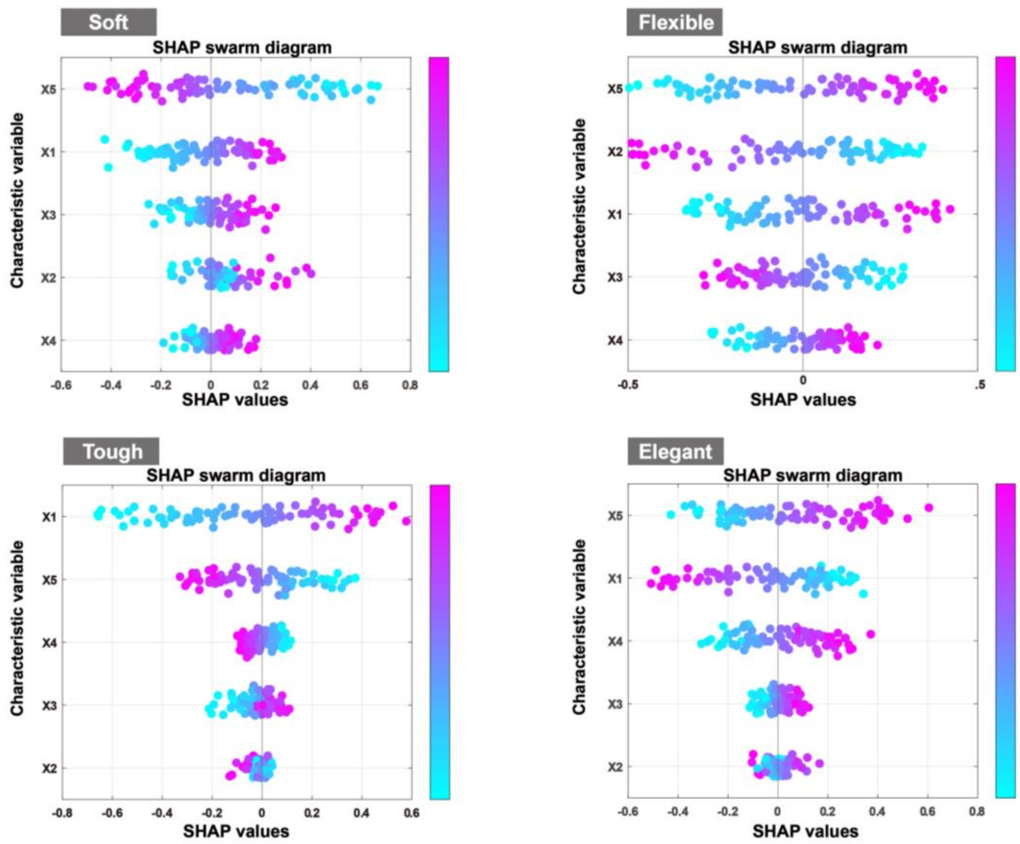

Fig. 7. SHAP swarm diagram

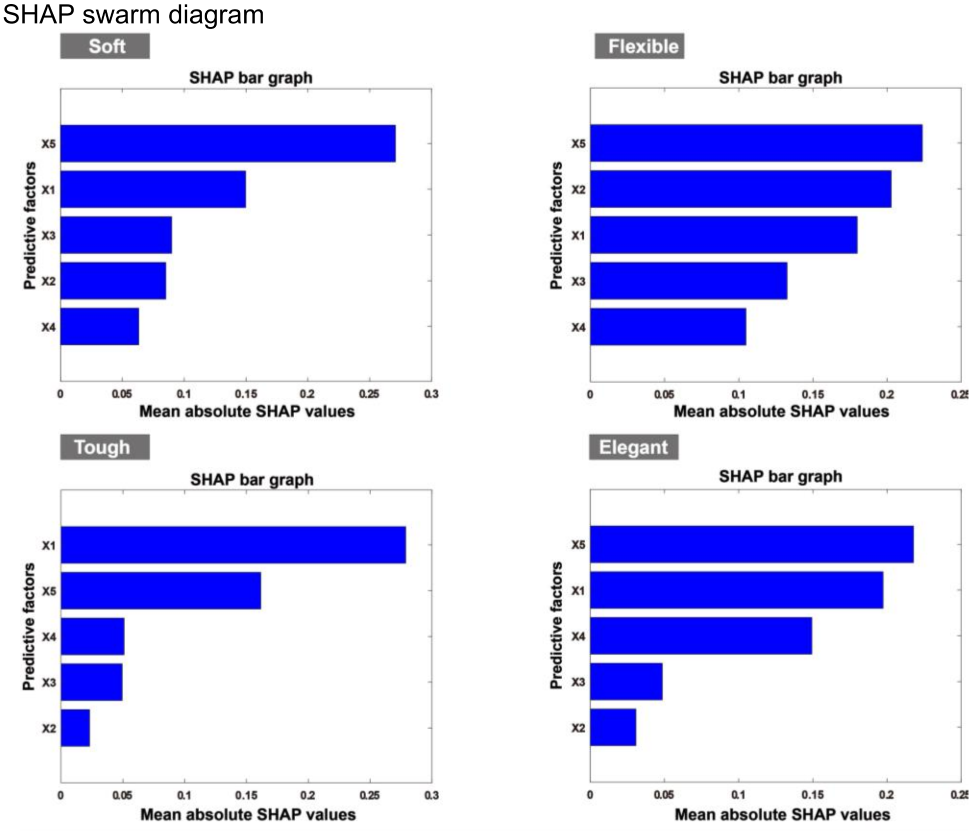

Fig. 8. SHAP bar graph

The users' demand of "flexible" is taken as an example; the validity of the proposed research framework is verified. The five design components extracted by the expert group have a total of 6×5×5×5×5=3750 design combinations. The design combination data set is encoded as GA-BPNN input layer parameters; and the corresponding Kansei evaluation is calculated by mapping model, among which the highest Kansei evaluation is 4.3368. The corresponding design combination parameter is (5,1,1,2,5); The feature parameters correspond to the backrest 5, seat cushion 1, support 2 and texture 5 in the morphological feature table. Based on the SHAP results, in the user emotion "flexible," the influence of "The way of bamboo-weaving" (X5) and "The seat surface" (X2) is the highest, making them the focal points of the design. "The back of the chair" (X1) and "The armrest" (X3) have a moderate level of influence and should still be considered during the design process. "The legs" (X4) have the lowest level of influence, and thus are not a primary consideration in the design process. Based on the optimal design parameter combination predicted by the GA-BPNN and the most influential design features identified through SHAP analysis, we have conducted a comprehensive design of the chair. AIGC is used to generate images and the key words of "flexible" and "bamboo chair" are added after repeated training to generate product images, as shown in Fig. 9. At the same time, this study carried out a detailed dimensional design of the bamboo chair based on ergonomic principles and constructed an accurate product model using Rhino7.5 3D modelling software. The design provides a reliable size reference basis for similar furniture, and its complete three-view display is shown in Fig. 10. With its unique design concept, the flexible bamboo chair shows the combination of nature and practicality. The curved backrest fits the curve of the body, which provides comfortable support. The folding handrail design is flexible and convenient for users to relax. The square cushion is simple and generous, which complements the warm texture of bamboo with each other. The support of the chair consists of four external expansion parts to ensure stability and sense of security. The skew cross bamboo weaving process enhances the robustness of the structure and at the same time, it gives the chair a light visual effect.

Fig. 9. "Flexible" Bamboo chair sensuous intentional design practice

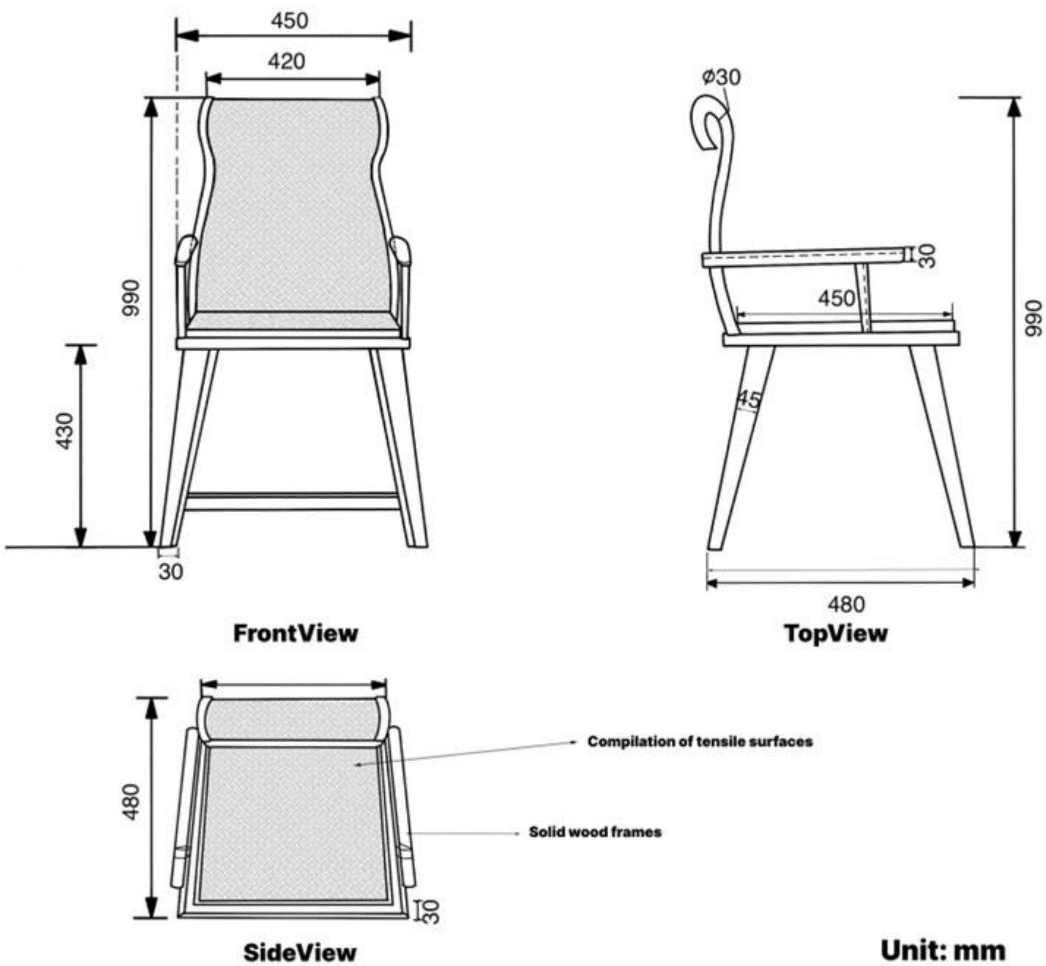

Fig. 10. “Flexible” Bamboo chair three views and dimensions

Finally, the questionnaire of flexible bamboo chairs’ Kansei design scheme was adopted by using the 7-step Likert scale. The perceptual evaluation study employed a rigorously designed 7-point Likert scale questionnaire (1 = "strongly disagree" to 7 = "strongly agree") to assess flexible bamboo chair designs, with 100 qualified participants (52 female, 48 male; aged 18-45) recruited through stratified sampling across three representative cohorts: 30% professional furniture designers, 40% frequent eco-friendly furniture consumers, and 30% home furnishing retail purchasers, all screened for minimum 2 years of furniture usage experience and material bias exclusion. The survey was administered under controlled environmental conditions *via* Credamo platform with attention-check questions, achieving an 83.6% response rate (107/128) with 7 invalid responses excluded. The resulting data showed excellent internal consistency (Cronbach's α = 0.89) and a mean Kansei score of 5.815 (SD = 0.71), significantly exceeding the predefined 4.25 threshold (one-sample t-test, $p < 0.001$, Cohen's d = 1.92), thereby statistically validating the framework's effectiveness for guiding emotionally resonant yet technically feasible product development. Product companies can use this research method as an important reference to guide the early stage of product design and development, thus meeting the emotional needs of users and improving consumers’ purchase willingness.

Despite the subjectivity and uncertainty of users' perceptions, the methodology proposed in this study is effective in ensuring that this uncertainty does not affect the physical feasibility of the final furniture design. Throughout the design process, we first determined the basic structure of the furniture before guiding the user to generate perceptual awareness. In other words, core structural factors such as support methods, connecting nodes and material bearing paths are locked in as a stable design foundation before entering the perceptual feedback process of user engagement. In addition, this study utilises RST to systematically deal with perceptual ambiguities, while GA-BPNN and SHAP to steer the design search space in a direction that is both desirable and practically achievable. Parametric constraints are used throughout the model design process to ensure manufacturability and functional robustness. This internal stability structure is maintained during the conceptual design generation phase. The system introduces consumer preferences and perceptual characteristics only to the extent that this structure allows for personalised expression. The final output is not just an aesthetic presentation, but an optimised result of user perception, designer's professional judgement and structural feasibility. Through this systematic modelling and constraint mechanism, this study ensures that the generated furniture design solutions are still structurally sound and feasible in actual manufacturing and usage scenarios, while achieving personalisation and innovation.

RESULTS AND DISCUSSION

KE is taken as the research framework, RST is combined with GA-BPNN in this study to develop the shape design method of bamboo furniture; the bamboo chair is taken as the research object to verify the feasibility of the method. The proposed method is universal and targeted. Specific emotional needs can be collected for different target user groups; the corresponding product features can be deconstructed for different design objects. The RST attribute reduction algorithm can help designers extract the emotional needs with the highest user satisfaction from many needs; and the direction of product design is clarified. The morphological deconstruction method is used to deconstruct product design components. GA-BPNN is used to establish a mapping model between key emotional needs and components, which can predict product design parameters in line with users' emotional preferences. Thus, the emotional semantics of products can be improved.

Comparison of Extracting Kansei Needs Between Rough Set Theory and Traditional Methods

In the contemporary product environment, identifying the emotional needs of users has become increasingly important. With the intensification of market competition and the improvement of consumer expectations, simply focusing on the functionality of products can no longer meet the increasingly diversified needs of users. Emotional needs not only affect users' satisfaction with products, but also directly relate to brand loyalty and market competitiveness. Therefore, in-depth understanding and accurate extraction of users' emotional needs is an indispensable part of the product design and development process. Many scholars have proposed different methods to extract users' emotional needs. For example, Analytic Hierarchy Process (AHP) (Zuo and Wang 2020) is widely used to build decision models and assign weights to various emotional factors through expert evaluation. However, this approach is often influenced by subjective judgment, which can lead to inconsistent results. In addition, factor analysis is also used to identify potential emotional factors and simplify complex information through data dimensionality reduction, but its effectiveness depends on sample size and data quality. Grey correlation analysis (GRA) evaluates the importance by calculating the correlation degree between emotional factors and ideal solution; but it also faces the problem of subjectively selecting reference sequences and it is difficult to deal with fuzzy and uncertain information (Zhou *et al*. 2023b). In contrast, RST has obvious advantages in extracting emotional needs. RST can effectively deal with the uncertainty and ambiguity in the data; and it can analyze the relationship between different attributes through the decision table to reveal the potential correlation. In addition, it does not rely on prior knowledge, thus reducing the impact of subjective biases on the results. It can also screen out the most influential emotional needs, which simplifies the analysis process. Therefore, in face of complex and changeable users' needs, RST provides a more comprehensive, objective and flexible method for demand extraction in KE.

Comparison between GA-BPNN and Traditional Kansei Mapping Model

After determining the core components of product design, how to effectively connect these elements with users' Kansei needs is one of the core tasks of KE. Traditional Kansei models such as quality function deployment (QFD) (Dolgun and Köksal 2018), QT-1 model and fuzzy QFD, provide a structured approach to product design to a certain extent, but they also have some obvious shortcomings. Firstly, QFD is taken as an example. It guides product development by translating customer needs into technical requirements. However, QFD is often unable to deal with complex, multi-dimensional emotional needs because it relies on expert experience and subjective judgment, which can easily lead to information loss or misunderstanding. Although QT-1 model introduces quantitative analysis, it lacks flexibility in face of dynamic market demand changes. Although fuzzy QFD tries to deal with uncertainty through fuzzy logic, its calculation process is complicated and it is difficult to realize efficient data processing. With the development of artificial intelligence technology, many emerging methods such as BPNN (Wang *et al*. 2024) and support vector regression (SVR) (Lian *et al*. 2022; Ren *et al*. 2025) have been gradually introduced into the construction of Kansei mapping model. As a typical machine learning, BPNN can establish a nonlinear relationship between input and output through learning historical data. However, BPNN is easy to fall into the local optimal solution during training and it is very sensitive to the selection of hyper parameters, which may lead to the instability of model performance. SVR performs regression analysis by finding the best hyper plane; and it performs well in processing small samples and high-dimensional data, but it has high requirements for kernel function selection and parameter adjustment; and it has low computational efficiency on large-scale data sets. Compared with the above methods, the GA-BPNN shows more significant advantages. GA is an optimization algorithm based on natural selection and genetics. It stimulates the mechanisms of selection, crossover and mutation in the process of biological evolution; and it gradually evolves better solutions by evaluating the fitness of individual solutions. The combination of genetic algorithm and BP neural network to form GA-BPNN can give full to the advantages of both sides. Specifically, GA-BPNN firstly uses genetic algorithm to optimize the structure and weight of BP neural network. In this process, the selection, crossover and mutation of GA are carried out by evaluating the fitness of multiple individuals (namely different network configuration) to find the best combination of network parameters. This method not only improves the convergence speed of BPNN in the training process, but also enhances the prediction ability of the model. When constructing Kansei mapping models, GA-BPNN can more effectively capture the complex relationship between design elements and Kansei requirements; and it can provide more accurate and reliable prediction results. In this study, the results of the perceptual evaluation data were brought into the BPNN and SVR isofunctional models for quantitative comparison with GA-BPNN.

Table 8 shows the comparative performance of SVR, BPNN, and GA-BPNN models in predicting four key Kansei attributes (Flexible, Soft, Tough, Elegant) across training and test sets. The GA-BPNN hybrid model demonstrates remarkable optimization capability in training scenarios, achieving the highest average R^2 (0.944) and lowest RMSE (0.154) among all models, indicating exceptional learning capacity and parameter optimization. In comparison, the R^2 of GA-BPNN is significantly higher than that of SVR (training set +14.98%, test set +16.73%) and BPNN (training set +8.26%, test set +12.29%), indicating stronger model explanatory power. The RMSE (Root Mean Square Error) of GA-BPNN is approximately 50%~55% lower than that of SVR and 42%~45% lower than that of BPNN, indicating a significant reduction in prediction errors. In summary, when constructing Kansei mapping model, GA-BPNN not only overcomes some inherent defects of BPNN but also improves the performance of the model in practical applications compared with traditional methods and other modern machine learning technologies. It also provides a more effective solution for the field of KE.

Table 8. Comparison of Mapping Model Parameter Results of BPNN and SVR with GA-BPNN

Kansei needs	Test set fitting data		Training set fitting data	
	R^2 (avg)	RMSE (avg)	R^2 (avg)	RMSE (avg)
SVR	0.783	0.312	0.821	0.285
BPNN	0.814	0.267	0.872	0.231
GA-BPNN	0.914	0.154	0.944	0.126

CONCLUSIONS

1. In this study, Genetic Algorithm-Backpropagation Neural Networks (GA-BPNN) is used to construct a mapping model between design elements and emotional needs. The evaluation results of the subjects show that it is significantly higher than the mean value, which improves the emotional semantics of products and proves the feasibility of the proposed research framework.
2. A Kansei Engineering (KE) model combining Rough Set Theory (RST), GA-BPNN and Shapley Additive Explanations (SHAP) is proposed to optimize the AI-assisted method of product shape design.
3. RST attribute reduction algorithm is used instead of the traditional method to extract the key users' emotional needs, which provides a more efficient and accurate method for this field. Thus, the designer can accurately grasp the users' needs. At the same time, SHAP interpretability analysis is used to examine the functioning mechanism of the GA-BPNN, revealing which design parameters are key factors influencing user emotions.
4. In this study, KE words are used as a summary in the extraction of users' emotional needs and are limited to simple adjectives and do not accurately describe complex

emotional needs. In the future, it is suggested to consider introducing physiological instruments such as eye tracker, electroencephalogram to comprehensively measure users' emotional needs.

REFERENCES CITED

Achar, C., So, J., Agrawal, N., and Duhachek, A. (2016). "What we feel and why we buy: The influence of emotions on consumer decision-making," *Current Opinion in Psychology* 10, 166-170. DOI: 10.1016/j.copsyc.2016.01.009

Akgül, E., Özmen, M., Aydoğan, E. K., and Sinanoğlu, C. (2020). "Baby cradle design with Kansei knowledge mining based on rough set theory," *Customer Oriented Product Design: Intelligent and Fuzzy Techniques*, 469-478. DOI: 10.1007/978-3-030-42188-5_24

Al-Jarrah, R., and AL-Oqla, F. M. (2022). "A novel integrated BPNN/SNN artificial neural network for predicting the mechanical performance of green fibers for better composite manufacturing," *Composite Structures* 289, 115475. DOI: 10.1016/j.compstruct.2022.115475

Al Hamli, S. S., and Sobaih, A. E. E. (2023). "Factors influencing consumer behavior towards online shopping in Saudi Arabia amid covid-19: Implications for E-businesses post pandemic," *Journal of Risk and Financial Management* 16(1), 36. DOI: 10.3390/jrfm16010036

Bai, L., Song, C., Zhou, X., Tian, Y., and Wei, L. (2023). "Assessing project portfolio risk *via* an enhanced GA-BPNN combined with PCA," *Engineering Applications of Artificial Intelligence* 126, 106779. DOI: 10.1016/j.engappai.2023.106779

Cai, M., Wu, M., Luo, X., Wang, Q., Zhang, Z., and Ji, Z. (2023). "Integrated framework of Kansei engineering and Kano model applied to service design," *International Journal of Human–Computer Interaction* 39(5), 1096-1110. DOI: 10.1080/10447318.2022.2102301

Chen, W. (2022). "Research on furniture design integrating Ming-style furniture modeling elements and image sensor data: Taking suitable old furniture as an example," *Journal of Sensors* 2022(1), 5306491. DOI: 1155.2022/5306491/3

Chen, Z. (2024a). "An elderly-oriented design of HMI in autonomous driving cars based on rough set theory and backpropagation neural network," *IEEE Access* 12, 26800-26818. DOI: 10.1109/ACCESS.2024.3366548

Chen, Z. (2024b). "An elderly-oriented form design of low-speed new energy vehicles based on rough set theory and support vector regression," *World Electric Vehicle Journal* 15(9), 389. DOI: 10.3390/wevj15090389

Deng, W., Lin, H., and Jiang, M. (2023). "Research on bamboo furniture design based on D4S (Design for Sustainability)," *Sustainability* 15(11), 8832. DOI: 10.3390/su15118832

Dolgun, L. E., and Köksal, G. (2018). "Effective use of quality function deployment and Kansei engineering for product planning with sensory customer requirements: A plain yogurt case," *Quality Engineering* 30(4), 569-582. DOI: 10.1080/08982112.2017.1366511

Fan, Y., Zhu, Z., Luan, J., and Liu, Y. (2024). "Exploring the application method of bamboo powder in promoting the development of sustainable outdoor furniture," *Sustainability* 16(24), 11282. DOI: 10.3390/su162411282

Fu, B., Guo, Z., Yan, J., Sun, L., Zhang, S., and Nie, L. (2023). "Research on the heat extraction performance optimization of spiral fin coaxial borehole heat exchanger based on GA–BPNN–QLMPA," *Processes* 11(10), 2989. DOI: 10.3390/pr11102989

Fu, L., Lei, Y., Zhu, L., Yan, Y., and Lv, J. (2024). "Integrating Kansei engineering with hesitant fuzzy quality function deployment for rosewood furniture design," *BioResources* 19(3), 6403-6426. DOI: 10.15376/biores.19.3.6403-6426

Ge, B., Shaari, N., Yunos, M. Y. M., and Abidin, S. Z. (2023). "Group consumers' preference recommendation algorithm model for online apparel's colour based on Kansei engineering," *Industria Textila* 74(1), 81-89. DOI: 10.35530/IT.074.01.202268

Ginting, R., Ishak, A., Malik, A. F., and Satrio, M. R. (2020). "Integration of Kansei engineering and quality function deployment (QFD) for product development: a literature review," in: *2nd International Conference on Industrial and Manufacturing Engineering (ICI&ME 2020)*, Medan, Indonesia. DOI: 10.1088/1757-899X/1003/1/012020

Hartono, M., Prayogo, D. N., Ronyastra, I. M., and Baredwan, A. (2024). "Kansei engineering with online review mining methodology for robust service design," *Theoretical Issues in Ergonomics Science* 25(4), 495-520. DOI: 10.1080/1463922X.2023.2261995

Hu, P., Lu, Y., and Wang, B. (2022). "Experiencing power over AI: The fit effect of perceived power and desire for power on consumers' choice for voice shopping," *Computers in Human Behavior* 128, 107091. DOI: 10.1016/j.chb.2021.107091

Jiang, Z., Gan, J., Hong, V., and Wu, B. (2024). "Application of Kansei engineering in the innovative design of traditional fashion elements," *Industria Textila* 75(3), 289-301. DOI: 10.35530/IT.075.03.202370

Kang, X. (2021). "Combining rough set theory and support vector regression to the sustainable form design of hybrid electric vehicle," *Journal of Cleaner Production* 304, 127137. DOI: 10.1016/j.jclepro.2021.127137

Kang, X. (2024). "Biologically inspired product design combining Kansei Engineering and Association Creative Thinking Method," *Advanced Engineering Informatics* 62, 102615. DOI: 10.1016/j.aei.2024.102615

Li, S. (2024). "Integrating rough set theory and fuzzy association rule mining for product Kansei knowledge analysis," *Journal of Advanced Mechanical Design, Systems, and Manufacturing* 18(6), JAMDSM0081-JAMDSM0081. DOI: 10.1299/jamdsm.2024jamdsm0081

Li, X., and Li, H. (2024). "Age-appropriate design of domestic intelligent medical products: An example of smart blood glucose detector for the elderly with AHP-QFD Joint KE," *Heliyon* 10(5). DOI: 10.1016/j.heliyon.2024.e27387

Lian, W., Wang, K.-C., Li, Y., Chen, H.-Y., and Yang, C.-H. (2022). "Affective-blue design methodology for product design based on integral Kansei engineering," *Mathematical Problems in Engineering* 2022(1), 5019588. DOI: 1155.2022/5019588/1

Liang, Y., Jiang, K., Gao, S., and Yin, Y. (2022). "Prediction of tunnelling parameters for underwater shield tunnels, based on the GA-BPNN method," *Sustainability* 14(20), 13420. DOI: 10.3390/su142013420

Lin, J.-L., and Zheng, M.-C. (2024). "An empirical investigation on the visual imagery of augmented reality user interfaces for smart electric vehicles based on Kansei engineering and FAHP-GRA," *Mathematics* 12(17), 2712. DOI: 10.3390/math12172712

Lin, Z.-H., Woo, J.-C., Luo, F., and Pan, G.-Q. (2023). "Multisensory design of electric shavers based on Kansei engineering and artificial neural networks," *Mathematical Problems in Engineering* 2023(1), 1188537. DOI: 10.1155/2023/1188537

Liu, X., and Yang, S. (2022). "Study on product form design via Kansei engineering and virtual reality," *Journal of Engineering Design* 33(6), 412-440. DOI: 10.1080/09544828.2022.2078660

Nagamachi, M. (1995). "Kansei engineering: A new ergonomic consumer-oriented technology for product development," *International Journal of Industrial Ergonomics* 15(1), 3-11. DOI: 10.1016/0169-8141(94)00052-5

Pawlak, Z. (1998). "Rough set theory and its applications to data analysis," *Cybernetics and Systems* 29(7), 661-688. DOI: 10.1080/019697298125470

Qi, Y., and Kim, K. (2024). "Evaluation of electric car styling based on analytic hierarchy process and Kansei engineering: A study on mainstream Chinese electric car brands," *Heliyon* 10(5). DOI: 10.1016/j.heliyon.2024.e26999

Ramanathan, R., Abdullah, L., Fauadi, M. H. F. M., Mohamed, M. S. S., and Kamaludin, K. N. (2023). "A hybrid of Kansei Engineering (KE) and analytical hierarchy process (ahp) to develop conceptual designs of portable oil spill skimmer," *IIUM Engineering Journal* 24(1), 183-198. DOI: 10.31436/iiumej.v24i1.2426

Ren, X., Wang, N., Pan, J., and Bu, L. (2025). "Combining style generative adversarial networks with particle swarm optimisation-support vector regression to design affective social robot for public health intervention," *Journal of Engineering Design* 36(1), 160-190. DOI: 10.1080/09544828.2024.2415830

Sato, K., Ito, T., and Ishizu, S. (2022). "Novel Kansei design method based on rough set theory," in: *2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Kuala Lumpur, Malaysia, pp. 1237-1241. DOI: 10.1109/IEEM55944.2022.9989818

Scrucca, L. (2013). "GA: A package for genetic algorithms in R," *Journal of Statistical Software* 53, 1-37. DOI: 10.18637/jss.v053.i04

Shi, J., Xu, X., Zhong, T., Zhang, W., Yuan, S., Feng, X., Sang, R., Xia, C., Chen, H., Fei, B. (2023). "Fabrication and application of eco-friendly bamboo self-bonded composites for furniture," *ACS Sustainable Chemistry and Engineering* 11(20), 7833-7843. DOI: 10.1021/acssuschemeng.3c00721

Sun, A., Tang, X., Liao, H., and Gong, J. (2025). "Predicting ignitability classification of thermally thick solids using hybrid GA-BPNN and PSO-BPNN algorithms," *Fuel* 381, 133474. DOI: 10.1016/j.fuel.2024.133474

Thangavel, K., and Pethalakshmi, A. (2009). "Dimensionality reduction based on rough set theory: A review," *Applied Soft Computing* 9(1), 1-12. DOI: 10.1016/j.asoc.2008.05.006

Wang, C., Zhang, J., Liu, D., Cai, Y., and Gu, Q. (2024). "An AI-powered product identity form design method based on shape grammar and Kansei engineering: Integrating Midjourney and Grey-AHP-QFD," *Applied Sciences* 14(17), 7444. DOI: 10.3390/app14177444

Wang N, Shi D, Li Z, et al. Investigating emotional design of the intelligent cockpit based on visual sequence data and improved LSTM[J]. Advanced Engineering Informatics, 2024, 61: 102557.

Wang, T., Xu, M., Yang, L., Zhou, M., and Sun, X. (2024). "Constructing a MOEA approach for product form Kansei design based on text mining and BPNN," *Journal of Intelligent and Fuzzy Systems* (Preprint), 1-21. DOI: 10.3233/JIFS-230668

Wang, T., and Yang, L. (2023). "Combining GRA with a fuzzy QFD model for the new product design and development of Wickerwork Lamps," *Sustainability* 15(5), 4208. DOI: 10.3390/su15054208

Wu, Y., Wu, D., Fei, M., Sørensen, H., Ren, Y., and Mou, J. (2023). "Application of GA-BPNN on estimating the flow rate of a centrifugal pump," *Engineering Applications of Artificial Intelligence* 119, 105738. DOI: 10.1016/j.engappai.2022.105738

Yang, C., Liu, F., and Ye, J. (2023). "A product form design method integrating Kansei engineering and diffusion model," *Advanced Engineering Informatics* 57, 102058. DOI: 10.1016/j.aei.2023.102058

Yang, C., Xu, T., and Ye, J. (2024). "Applying TRIZ and Kansei engineering to the eco-innovative product design towards waste recycling with latent Dirichlet allocation topic model analysis," *Engineering Applications of Artificial Intelligence* 133, 107962. DOI: 10.1016/j.engappai.2024.107962

Yu, S., Zhong, Z., Zhu, Y., and Sun, J. (2024). "Green emotion: Incorporating emotional perception in green marketing to increase green furniture purchase intentions," *Sustainability* 16(12), 4935. DOI: 10.3390/su16124935

Yuan, T., Wang, X., Liu, X., Lou, Z., Mao, S., and Li, Y. (2022). "Bamboo flattening technology ebables efficient and value-added utilization of bamboo in the manufacture of furniture and engineered composites," *Composites Part B: Engineering* 242, 110097. DOI: 10.1016/j.compositesb.2022.110097

Zhang, Q., Xie, Q., and Wang, G. (2016). "A survey on rough set theory and its applications," *CAAI Transactions on Intelligence Technology* 1(4), 323-333. DOI: 10.1016/j.trit.2016.11.001

Zhang, S., Zhu, J., Wang, G., Reng, S., and Yan, H. (2022). "Furniture online consumer experience: A literature review," *BioResources* 17(1), 1627-1642. DOI: 10.15376/biores.17.1.1627-1642

Zhao, X., Sharudin, S. A., and Lv, H.-L. (2024). "A novel product shape design method integrating Kansei engineering and whale optimization algorithm," *Advanced Engineering Informatics* 62, 102847. DOI: 10.1016/j.aei.2024.102847

Zhou, C., Gu, W., Luo, X., and Kaner, J. (2023a). "Building a 4E interview-grounded theory model: A case study of demand factors for customized furniture," *PLOS One* 18(4), e0282956. DOI: 10.1371/journal.pone.0282956

Zhou, C., Jiang, L., and Kaner, J. (2023b). "Study on imagery modeling of electric recliner chair: based on combined GRA and Kansei engineering," *Applied Sciences* 13(24), 13345. DOI: 10.3390/app132413345

Zimo, C., Hailong, F., and Yajun, L. (2024). "A front face design of new energy vehicles based on rough set theory and backpropagation neural network," *Kansei Engineering* 145(145). DOI: 10.54941/ahfe1005142

Zuo, Y., and Wang, Z. (2020). "Subjective product evaluation system based on Kansei engineering and analytic hierarchy process," *Symmetry* 12(8), 1340. DOI: 10.3390/sym12081340

Article submitted: February 10, 2025; Peer review completed: April 5, 2025; Revisions accepted: June 23, 2025; Published: July 8, 2025.
DOI: 10.15376/biores.20.3.7107-7133