Generative Design of Bamboo Furniture Combining Game Theory and AI-Generated Content

Jing Liu,[a] Honghe Gao,[a,b,]* and Olga Yezhova [b]

*Corresponding author: redriver@lnpu.edu.cn

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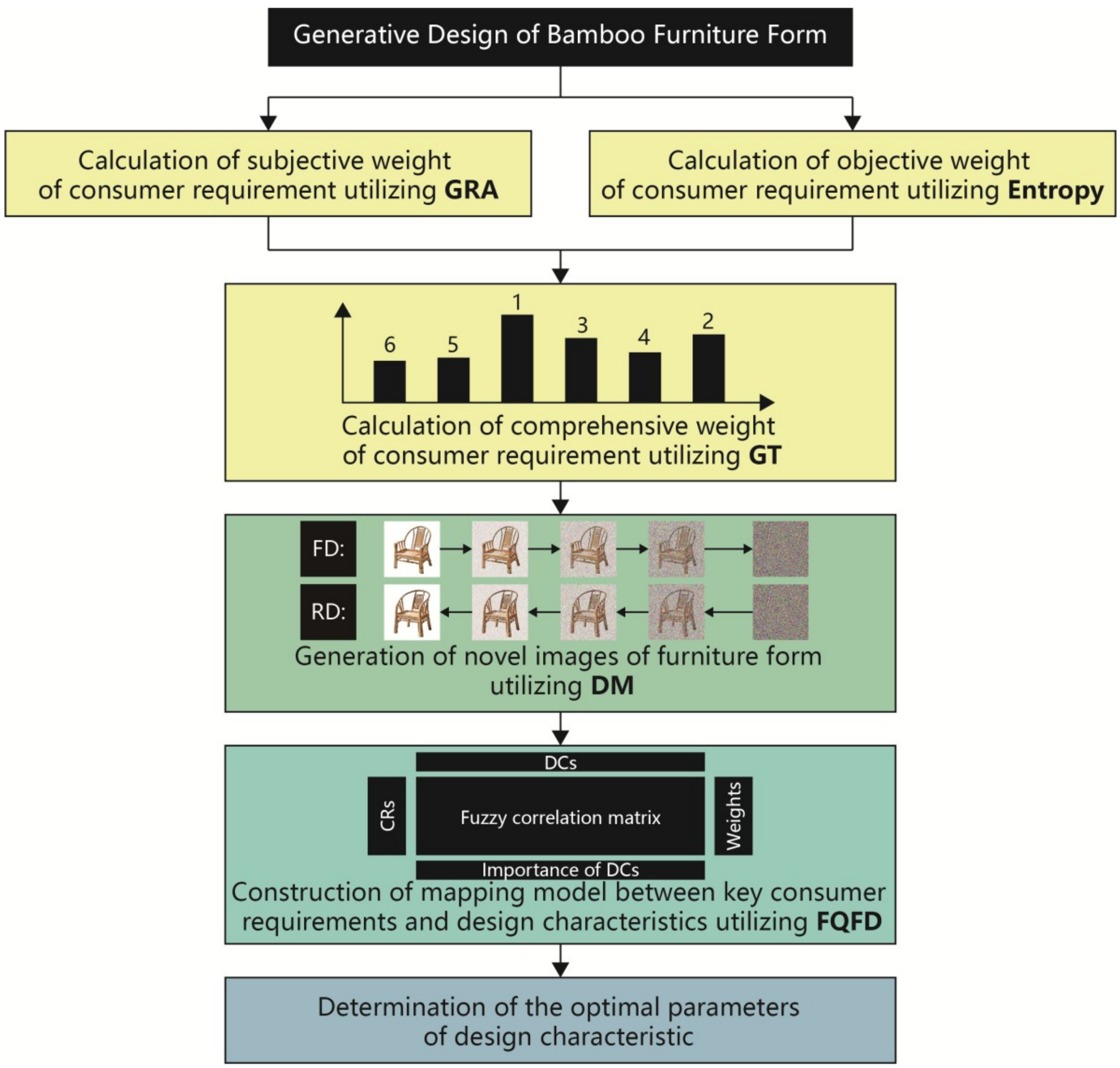
GRAPHICAL ABSTRACT



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Consumers tend to purchase and use furniture products that fulfill their emotional needs. However, existing bamboo furniture design departments lack a systematic and scientific approach to morphological design, and their innovation capabilities remain insufficient. This study proposes a generative design method for bamboo furniture that integrates Game Theory (GT) with AI-Generated Content (AIGC), grounded in Kansei Engineering. This approach aims to assist design departments in developing creative products that align with consumers' emotional needs, thereby fostering sustainable consumption and advancing the bamboo furniture industry. First, consumer-driven Kansei words were collected and categorized. Then, subjective and objective weight values of consumer requirements were calculated using Grey Relational Analysis (GRA) and entropy, respectively. Based on GT, a comprehensive weight value was determined to accurately identify key consumer requirements. Next, Diffusion Models in AIGC technology were employed to generate new furniture images, followed by morphological deconstruction. Finally, a House of Quality based on Fuzzy Quality Function Deployment was constructed to establish the mapping relationship between key consumer requirements and new morphological elements, determining the optimal furniture design parameters. The proposed method integrates the strengths of both subjective and objective approaches, enhancing the accuracy and scientific rigor of design decision-making.

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Keywords: AI-generated content; Generative design; Bamboo furniture; Game theory; Diffusion model; Fuzzy quality function deployment

*Contact information: a: Liaoning Petrochemical University, Dandong Road West Section, 1, 113001 Fushun, China; b: Kyiv National University of Technologies and Design, Kyiv Povitroflotskyi Prospekt, 31, 03037 Kyiv, Ukraine; *Corresponding author: redriver@lnpu.edu.cn*

INTRODUCTION

The rapid advancement of human society has been accompanied by the accelerating depletion of Earth's finite resources. In response to this, the furniture industry has increasingly turned to synthetic materials such as plastics, metals, and adhesives to replace traditional biomass materials. While these materials offer benefits such as cost efficiency and design flexibility, their non-biodegradable and non-renewable characteristics contribute to environmental pollution and the depletion of natural resources. In contrast, bamboo, which grows more rapidly than wood (Sofiana *et al*. 2018), serves as a rapidly renewable and sustainable biological resource (Dlamini *et al*. 2022). Furthermore, bamboo's superior mechanical strength and bending resistance have led to its growing adoption by designers in the furniture design and manufacturing industries (Sharma and van der Vegte 2020). Recently, the Chinese government, in partnership with the

International Bamboo and Rattan Organization, launched the “Bamboo for Plastic” initiative, aimed at reducing plastic pollution. Bamboo furniture is included in the initiative's primary product catalog. Using bamboo as a base material for furniture not only reduces production costs and supports cleaner manufacturing processes, but it also offers environmentally friendly alternatives for consumers.

In recent years, there has been a growing consumer preference for eco-friendly, affordable, and durable bamboo furniture. However, the bamboo furniture industry still lacks a comprehensive and systematic approach to form design. Many of these products fail to address the emotional needs of consumers, leading to a mismatch between market offerings and consumer expectations. This can result in limited consumer approval. Bamboo furniture that aligns with consumer aesthetics is more likely to enhance acceptance. Furthermore, many manufacturers continue to prioritize structural and functional improvements (Kang *et al*. 2023), such as craftsmanship, while neglecting the significant role that product form plays in the consumer market. In the context of the experience economy, consumers increasingly seek to fulfill their emotional needs, and product form plays a critical role in shaping their initial perceptions (Norman 2007). Meeting these needs has thus become a key determinant of a company’s market competitiveness (Shieh *et al*. 2018). Recent studies have begun to explore how bamboo furniture design can address the evolving demands of consumers. For example, Deng *et al*. (2023), drawing on the D4S theory, analyzed bamboo as an environmentally friendly material in furniture design. Cheng *et al*. (2020) conducted human factors experiments to examine how design parameter changes in bamboo lounge chairs affect user comfort. Zheng and Zhu (2021) analyzed contemporary aesthetic trends in bamboo furniture design through survey data and recommended that designers pay more attention to consumer preferences related to aesthetics. While these studies have broadened the theoretical understanding of bamboo furniture design, few have examined form design from the perspective of consumer emotional needs. To address these challenges, this study focuses on meeting consumers’ emotional needs by introducing Kansei Engineering as the core theoretical foundation. It leverages advanced AI-Generated Content (AIGC) technology to generate innovative furniture designs, identifies key user requirements, and translates them into design features. Through this approach, a generative design framework for bamboo furniture is established, fostering sustainable consumption within the furniture industry.

Kansei Engineering (KE) represents an extension of ergonomics, applying engineering techniques to translate consumers’ emotional responses to products into specific design features (Nagamachi 1995). KE has been successfully employed by companies such as Mazda, Canon, and Samsung in the development of new products, underscoring its importance in the experience economy. Within this context, accurately identifying and addressing consumer emotional needs has become a crucial factor for companies aiming to succeed in the marketplace. However, despite the advantages of KE in aligning with consumer preferences, primary limitations remain that require further refinement.

The first challenge lies in effectively identifying the truly critical user needs from a broad spectrum of consumer demands, enabling the precise definition of product lines during the early stages of development. Existing research often relies on subjective methods for assigning weights to user needs. While these methods are practical, their heavy reliance on expert judgment can undermine the objectivity of decision-making. Common techniques include the Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), and Analytic Network Process (ANP). For example, Yang *et al*. (2023a) employed factor analysis to reduce the dimensionality of emotional vocabulary in product form design, followed by the application of AHP to calculate the subjective weights of these terms. Liu *et al*. (2024) used FAHP to rank various factors in intelligent vehicle development, supporting the improvement of car interiors. To overcome these limitations, this study proposes an integrated approach that combines both subjective and objective methods. By applying Game Theory (GT), subjective and objective weights are synthesized to generate a comprehensive weight for user requirements, leading to a more precise identification of critical needs. Game Theory (Tang *et al*. 2025), a field of modern mathematics, offers a method for determining optimal equilibrium solutions between two or more participants, thereby maximizing collective benefits.

Traditional morphological analysis methods can only generate product forms that already exist in the market, failing to address the issue of design homogeneity. With the advent of the artificial intelligence era, various AI algorithms have been applied to design-related tasks such as data analysis, emotion recognition, and image generation, enhancing the accuracy and objectivity of design decision-making. AI-Generated Content (AIGC) provides technical support for rapidly generating diverse product concepts, significantly improving design efficiency. For instance, Tang *et al*. (2025) integrated Generative Adversarial Networks (GANs) with color labels in hairdryer design, producing highly realistic color effects. However, GANs rely on adversarial learning between the generator and discriminator networks, which often results in limited diversity in the generated images. To assist designers in creating high-quality and diverse furniture products, this study introduces the Diffusion Model (DM) (Ho *et al*. 2020) within AIGC technology. This model has outperformed GANs in image synthesis and holds significant potential for further development.

Once key user requirements have been identified, accurately translating these needs into design features becomes a fundamental challenge in KE research. Traditionally, most studies employ linear regression models to establish mathematical relationships between user needs and design features. However, such models assume a simple linear relationship between variables, which fails to capture the inherent fuzziness of user perceptions. For instance, Smith and Fu (2011) used Quantification Theory Type-1 to create predictive models linking representative Kansei factors with Head-Up Display (HUD) image design attributes, addressing the emotional needs of drivers. Similarly, Chen and Cheng (2020) applied multiple linear regression to define the mathematical relationship between emotional vocabulary and design elements for career women’s vest styles, successfully predicting consumer perceptions. To address these limitations, this study proposes the use of Fuzzy Quality Function Deployment (FQFD) to develop a mapping model between key user requirements and design features. FQFD, an extension of Quality Function Deployment (QFD) (Khoo and Ho 1996), integrates fuzzy mathematics to more accurately represent the nuanced emotional evaluations of users.

This study makes three primary contributions: (1) Leveraging the diffusion model (DM) in AIGC to train and generate diverse furniture images, enhancing the creativity of design features; (2) It replaces traditional subjective methods with GT, combining both subjective and objective user information to calculate a comprehensive weight value, thereby accurately identifying the most critical user needs; (3) FQFD is employed to create a fuzzy mapping model between key consumer requirements(CRs) and design characteristics(DCs), enabling the determination of optimal design parameters.

Table 1. Comparison and Summary of this Study with Previous Research

References	Key CRs	Mapping Model between CRs and DCs	Research Objective
This paper	GT, GRA, Entropy	FQFD	Bamboo furniture
(Smith and Fu 2011)	FA, CA	QTT-1	Head-up display
(Chen and Cheng 2020)	Expert evaluation	MLR	Female vest
(Wang *et al*. 2023)	GST	Grey-QFD	Security camera
(Li and Li 2024)	AHP	QFD	Smart blood glucose detector
(Kirgizov and Kwak 2022)	Kano's model	QFD	Automobile interior
(Kang and Nagasawa 2023)	CFKM	FQFD	Hybrid electric vehicle

Note: CRs: consumer requirements, DCs: design characteristics, FA: factor analysis, CA: cluster analysis, GST: grey system theory, QTT-1: quantification theory type 1, MLR: multiple linear regression, GRA: grey relational analysis, CFKM: continuous fuzzy kano's model, QFD: quality function deployment

LITERATURE REVIEW

AI-Generated Content

AIGC technology generates relevant content by learning and training on existing data. The emergence of algorithms such as Variational Autoencoder (VAE) and Generative Adversarial Networks (GAN) have significantly advanced the field. Among AIGC technologies, GAN and its various variants can produce highly realistic images, thereby greatly expanding designers' creative potential. For example, Jiang *et al*. (2023) employed BézierGAN in biomimetic design to generate high-performance flapping wing shapes. Although GAN is a classic deep generative model, its training and generation processes are complex. The generator and discriminator must reach Nash equilibrium, which is often unstable. Furthermore, because GAN-generated images must deceive the discriminator, they tend to have limited diversity.

The diffusion model (DM) (Dhariwal and Nichol 2021), on the other hand, generates high-quality images by training through a forward noise-adding process and a reverse denoising process. This approach results in more stable training and enables the generation of images with greater quality and diversity. Reports on the application of DM in design are emerging; for instance, Yang *et al*. (2023a) trained a DM to generate new product forms, enhancing design diversity and ultimately constructing a mapping model using SVR. Given that DM outperforms traditional GANs in terms of quality, diversity, and stability, this study applies DM to the generation of innovative bamboo furniture forms.

Game Theory

GT falls within the domain of operations research and has widespread applications in fields such as military strategy, economics, and engineering. Each participant in a game aims to maximize their own benefits, and the goal of GT is to achieve a consensus among participants to maximize collective benefits. This outcome is known as Nash equilibrium (Lai *et al.* 2015). Although this theory is rarely applied to furniture form design, this study utilizes it to calculate the combined value of subjective and objective weights, as these two weights may be in conflict. This approach ultimately allows for a more accurate understanding of key user needs. For example, Lai *et al*. (2015) introduced GT into flood risk assessment to balance the conflict between subjective and objective weights and determine the combined weight. Qiu *et al*. (2022) used GT in product target image recognition to recalculate the weights of three network attributes.

Fuzzy Quality Function Deployment

FQFD (Yang *et al*. 2003) integrates fuzzy set theory with traditional QFD, enabling the expression of the inherent fuzziness in expert evaluation processes. This method is a multi-level analysis approach that converts customer or market requirements into design specifications, component characteristics, process requirements, and production demands. It serves as a systematic quantitative tool aimed at ensuring products or services align precisely with customer needs. Initially applied in product design, FQFD has recently been introduced into the field of KE. For example, Wang and Yang (2023) used GRA to identify key user requirements, and based on FQFD, successfully translated these requirements into product parameters for rattan lamps, thereby reducing ambiguity in the product development process. Kang and Nagasawa (2023) applied FQFD in hybrid electric vehicle design, converting emotional vocabulary into automotive exterior components and deriving the optimal vehicle configuration. Fan *et al*. (2020) employed FQFD to quantify and prioritize design alternatives in cloud-based design decision-making environments.

METHODS

The methodological steps proposed in this study are illustrated in Fig. 1. Many affective words representing consumer emotional requirements are collected initially, and the KJ method is used to filter out representative consumer requirements. The subjective and objective weight values of these representative requirements are then calculated using Grey Relational Analysis (GRA) and Entropy, respectively, with Game Theory (GT) applied to determine the comprehensive weight values. Next, a diffusion model (DM) is trained and used to generate new furniture images, followed by morphological analysis to decompose the design features of the newly created bamboo furniture. Finally, a fuzzy mapping model between key consumer requirements and design characteristics is constructed using the House of Quality (HoQ) in Fuzzy Quality Function Deployment (FQFD) to determine the optimal combination of design parameters. In the final stage, design practice is carried out, where the optimal solution is further refined through detailed design and 3D modeling, completing the closed-loop development process of bamboo furniture products.

Calculation of Subjective Weight of Consumer Requirements Utilizing GRA

GRA is employed to calculate the subjective weight values of representative consumer demands in this study. Overall satisfaction serves as the reference sequence (parent sequence), while all representative user demands are treated as comparison sequences (child sequences). The importance of each demand is determined by calculating its correlation with the satisfaction level. The specific steps are outlined as follows

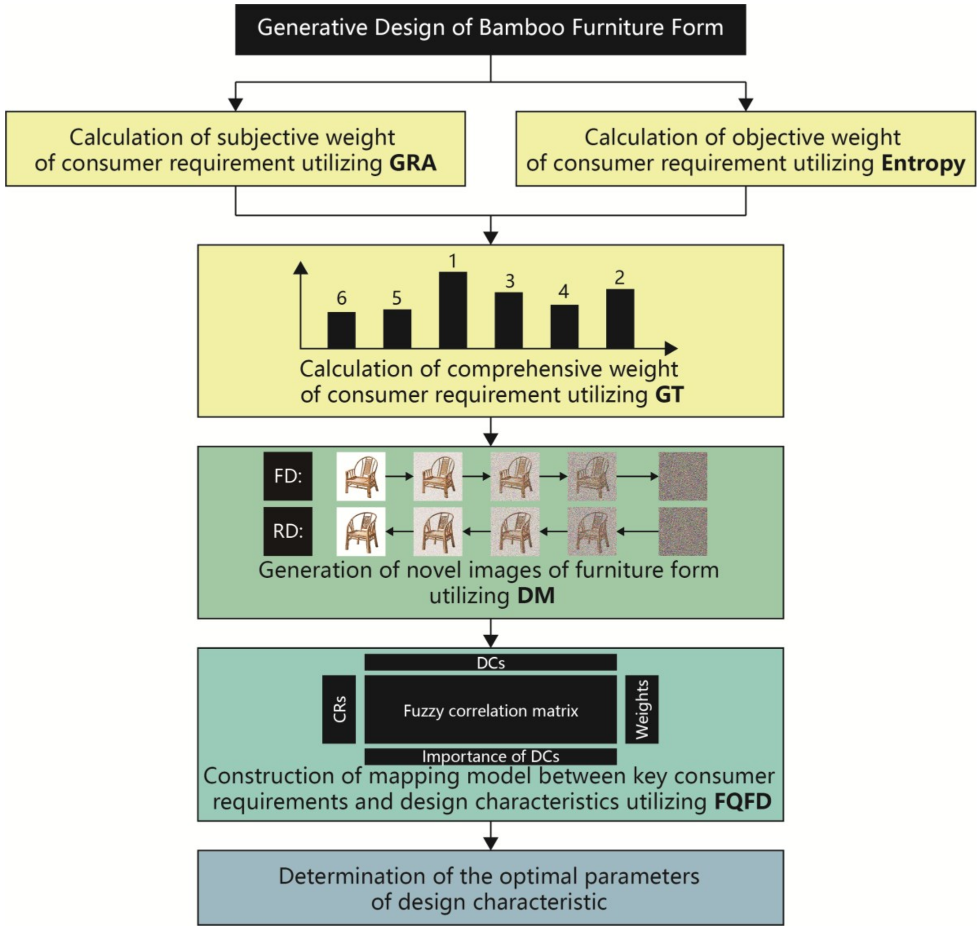


Fig. 1. Framework for generative design method of bamboo furniture

Step 1: Define the reference sequence and comparison sequences:

Let $X_o = (x_{oj} \mid j = 1, 2, \ldots, n)$ represent the reference sequence.

Let $X_i = (x_{ij} \mid j = 1, 2, \ldots, n)$ represent the comparison sequence, where i = 1, 2, …, m.

Step 2: Normalize the reference sequence data and comparison sequence data using Eqs. (1) and (2), respectively:

$$x_{oj}^{*} = \frac{x_{oj}}{\overline{x}_{oj}} \tag{1}$$

$$x_{ij}^{*} = \frac{x_{ij}}{\overline{x}_{ij}} \tag{2}$$

Step 3: Identify the difference sequences between the reference sequence and the comparison sequences, as shown in Eq. (3).

$$\Delta_{oij} = \mid x_{oj}^{*} - x_{ij}^{*} \mid, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n. \tag{3}$$

Step 4: Calculate the Grey relational coefficient using Eq. (4).

$$\gamma_{oij} = \frac{\min\limits_{\forall i}\min\limits_{\forall j}\Delta_{oij} + \zeta \max\limits_{\forall i}\max\limits_{\forall j}\Delta_{oij}}{\Delta_{oij} + \zeta \max\limits_{\forall i}\max\limits_{\forall j}\Delta_{oij}} \tag{4}$$

where ζ is the resolution factor, typically set to 0.5.

Step 5: Calculate the Grey relational grade for the comparison sequence indicators using Eq. (5). Finally, a relational grade to obtain the standardized subjective weights for consumer demands were normalized.

$$\Gamma_{oi} = \sum_{j=1}^{n} w_j \times \gamma_{oij}, w_j \text{ is the weight, } \sum_{j=1}^{n} w_j = 1 \tag{5}$$

Calculation of Objective Weight of Consumer Requirements Utilizing Entropy

User-reported decisions are inevitably influenced by personal subjectivity, leading to a lack of objectivity in the weight results. To address this, the Entropy-based objective weighting method effectively mitigates subjective factors. According to information entropy theory, the greater the dispersion of an indicator, the smaller its entropy value, which implies a higher weight for the indicator. In this study, Entropy is used to calculate the objective weight values for representative user demands. The specific steps are as follows:

Step 1: Construct the original data matrix *B* using Eq. (6), and then normalize the data using Eq. (7).

$$B = \left\{b_{ij}\right\}_{m\times n} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mn} \end{bmatrix}, i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{6}$$

$$p_{ij} = \frac{b_{ij} - \min(b_j)}{\max(b_j) - \min(b_j)} \tag{7}$$

In Eq. 7, p_{ij} represents the normalized value, and b_{ij} represents the original value.

Step 2: Calculate the weight and entropy values for each indicator. First, to avoid the occurrence of 0 or negative numbers in the data, a uniform non-negative shift is applied to the data matrix. In this study, the shift value is defined as 0.01, as shown in Eq. (8). Next, the weight for each indicator can be calculated using Eq. (9). Finally, the entropy value ej can be derived using Eq. (10).

$$p_{ij}^{*} = p_{ij} + 0.01 \tag{8}$$

$$p_{ij}^{**} = \frac{p_{ij}^{*}}{\sum_{i=1}^{m} p_{ij}^{*}}, j = 1,2,\ldots,n, i = 1,2,\ldots,m \tag{9}$$

$$e_j = -K\sum_{i=1}^{m}(p_{ij} \ln p_{ij}^{**}) \tag{10}$$

where K=1/ln(m).

The degree of dispersion d_j can be calculated using Eq. (11).

$$d_j = 1 - e_j, j = 1, 2, \ldots, n \tag{11}$$

Step 3: Use Eq. (12) to calculate the weight for each indicator.

$$w_j = \frac{d_j}{\sum_{k=1}^{m} d_k} d_j, j = 1, 2, \ldots, n \tag{12}$$

Calculation of Comprehensive Weight of Consumer Requirements Utilizing GT

The final step in determining the key CRs is to use GT to calculate the optimal equilibrium solution between the subjective and objective weight values, ultimately obtaining the comprehensive weight value. The specific steps of GT are as follows:
Step 1: Construct the weight vector set W using Eq. (13).

$$W = \sum_{k=1}^{L} a_k w_k^T (a_k > 0) \tag{13}$$

In Eq. 13, a_k represents the weight coefficient, w represents a possible weight vector from the set W, and L represents the number of weight vectors.

Step 2: Solve for the optimal solution of weight coefficient that minimizes the deviation from the subjective and objective weights.

$$\min \left\| \sum_{k=1}^{L} a_k w_k^T - w_i \right\|_2 \; (i = 1, 2, ..., L) \tag{14}$$

The optimal first-order derivative condition is as follows.

$$\sum_{k=1}^{L} a_k w_i w_k^T = w_i w_i^T \tag{15}$$

Step 3: Transform the equation into a system of linear equations using Eq. (16).

$$\begin{bmatrix} w_1 w_1^T & w_1 w_2^T & \ldots & w_1 w_L^T \\ w_2 w_1^T & w_2 w_2^T & \ldots & w_2 w_L^T \\ \vdots & \vdots & \ddots & \vdots \\ w_L w_1^T & w_L w_2^T & \ldots & w_L w_L^T \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_L \end{bmatrix} = \begin{bmatrix} w_1 w_1^T \\ w_2 w_2^T \\ \vdots \\ w_L w_L^T \end{bmatrix} \tag{16}$$

Step 4: Normalize the weight coefficients a using Eq. (17).

$$a_k^* = \frac{a_k}{\sum_{k=1}^{L} a_k} (k = 1, 2, \cdots, L) \tag{17}$$

Step 5: Calculate the comprehensive weight w^* using Eq. (18). Finally, based on the size of the comprehensive weight, rank the key consumer needs accordingly.

$$w^* = \sum_{k=1}^{L} a_k w_k^T \tag{18}$$

Generation of Novel Images of Furniture Form Utilizing DM

Diffusion Model is one of the latest advancements in AIGC technology. Unlike Generative Adversarial Networks (GANs), which require adversarial training between a generator and a discriminator, DM generates high-quality images through a process of adding and removing noise. Specifically, the noise-adding phase, known as the forward process, is used to construct training samples, while the noise-removal phase, known as the reverse process, is responsible for generating creative and high-quality images. The two diffusion processes of the DM are shown in Fig. 2.

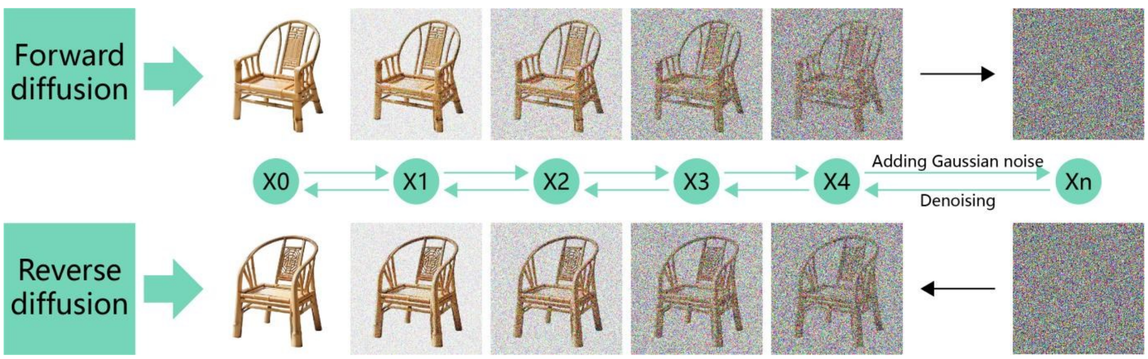


Fig. 2. The two diffusion processes of the DM

During the forward diffusion process, noise is gradually introduced into the images from the training dataset. By accumulating Gaussian noise over T iterations, the original real images are progressively transformed into completely noisy images. This process can be mathematically expressed using Eq. 19,

$$q(x_t | x_{t-1}) = N\left(x_t; \sqrt{1-\beta_t} x_{t-1}, \beta_t I\right), q(x_{1:T} | x_0) = \prod_{t=1}^{T} q(x_t | x_{t-1}). \tag{19}$$

where x_t represents the data at step t, and β_t denotes the noise level at step t.

The value of x_t in the forward process can be directly computed from x_0 and β. By setting $\alpha_t = 1-\beta_t$ and then defining $\bar{\alpha}_t = \prod_{i=1}^{T} \alpha_i$, the relationship between xt and x0 at any given time can be derived, as shown in Eq. 20:

$$q(x_t | x_0) = N(x_t; \sqrt{\bar{\alpha}_t} x_0, (1-\bar{\alpha}_t) I) \tag{20}$$

The reverse generation process generates images by gradually removing noise, restoring x_0 from pure noise.

$$p_\theta(x_{0:T}) = p(x_T) \prod_{t=1}^{T} p_\theta(x_{t-1} | x_t),\ p_\theta(x_{t-1} | x_t) = N(x_{t-1}; \mu_\theta(x_t, t), \sum\nolimits_\theta (x_t, t)) \tag{21}$$

In Eq. 21, μ_e and Σ_θ are the mean and variance of neural network parameterization respectively.

Construction of Mapping Model between Key Consumer Requirements and Design Characteristics Utilizing FQFD

The fundamental principle of FQFD aligns with that of QFD, but with the incorporation of triangular fuzzy sets within the traditional QFD framework. The central component of FQFD is the HoQ, which serves to precisely translate CRs into DCs while establishing the priority of DCs for furniture features.

Within the HoQ, the central matrix is employed to define fuzzy correlations, with the left wall representing user requirements and their comprehensive weight values, the ceiling representing the design feature parameters of bamboo furniture, and the floor indicating the importance and ranking of these design features.

Drawing upon the theoretical foundation laid by Cohen (1995), fuzzy correlation strengths are categorized into four levels, which are simplified through correlation symbols, as illustrated in Table 2.

The absolute importance of bamboo furniture design features is determined by both the comprehensive weight of user needs on the left wall of the HoQ and the strength of the correlations within the central matrix.

Table 2. Symbols of Triangular Fuzzy Numbers and Corresponding Definition in FQFD

Fuzzy Triangular Scale	Symbol	Definition
(0, 0, 0)	(unsigned)	No correlation
(1, 3, 5)	△	Weak correlation
(3, 5, 7)	○	Moderate correlation
(5, 7, 9)	●	Strong correlation

First, the Absolute Importance (AI) of the DCs is calculated using Eq. 22, followed by the determination of the Relative Importance of the design features using Eq. 23. Finally, the importance of the DCs is ranked on the floor of the House of Quality (HoQ) to identify the key DCs.

$$AI_j = \sum_{i=1}^{n} NW_i \otimes C_{ij} \tag{22}$$

$$RI_j = \frac{AI_j}{\sum_{j=1}^{m} AI_j} \tag{23}$$

In Eqs. 22 and 23, NW_i represents the comprehensive weight of the i-th CR derived from GT, C_y denotes the correlation between the i-th CR and the j-th DC, AI_j refers to the absolute importance of the j-th DC, and RI_j represents the relative importance of the j-th DC.

EXPERIMENTAL STUDY

Preliminary Preparation

On the one hand, consumers typically express their needs using natural language. To address this, the study gathered a comprehensive set of Kansei words representing CRs, ensuring the broad applicability of the acquired consumer demand through three primary sources: professional books, academic papers, and online consumer reviews. Subsequently, experts with extensive experience in product design research were invited to evaluate these consumer needs, retaining only those that reflected positive expectations, as these represented the desired user experience with furniture. The KJ method was then applied to categorize the CRs, ensuring no redundancy or similarity in meanings, ultimately retaining six key representative requirements: elegance, natural, stable, simple, beautiful, and soft.

Calculation of Subjective Weight of Consumer Requirements Utilizing GRA

The first step in identifying key consumer requirements is to collect user evaluation reports and construct a data matrix. The Likert scale, a psychometric tool developed by American sociologist Rensis Likert in the 1930s, is effective in quantifying respondents' perceptions of specific objects or phenomena. It has been widely used in fields such as social sciences, market research, and industrial design. Due to its simplicity and effectiveness, many scholars have adopted this method in Kansei engineering to evaluate product forms and quantify user emotions. Therefore, this study employs a 7-point Likert scale to effectively and precisely capture users' emotional evaluations and satisfaction levels with bamboo furniture. Scores of 1, 4, and 7 respectively represent "strongly disagree/dissatisfied," "neutral," and "strongly agree/satisfied." First, this study collected a large number of bamboo furniture image samples from professional books, academic papers, and online shopping platforms. Then, a focus group consisting of experts in industrial design and furniture design research was invited to examine and screen all the samples. This ensured that the final selection featured distinct morphological differences and that the furniture structures were reasonable, retaining only chairs with safe design. Additionally, since an excessive number of samples would significantly increase the time required for respondents to complete the questionnaire—potentially leading to impatience or negative emotions that could affect response quality—only ten representative bamboo furniture images were ultimately selected to ensure the reliability of the collected data. To ensure the accuracy of user responses in the questionnaire, interfering factors such as color, saturation, and product shadows were eliminated. All images were converted to grayscale using Adobe Photoshop, shadows were removed, and the final images were standardized to A4 size. Next, the ten bamboo furniture images and six representative Kansei words were used to develop a questionnaire based on the 7-point Likert scale. A total of 70 participants with prior experience using bamboo furniture were recruited. The questionnaire was distributed online, and participants could complete it *via* computer or smartphone. After screening the returned questionnaires, 61 valid responses were retained. These 61 valid participants represented a broad cross-section of the general population in terms of age (ranging from 18 to 60), gender (31 males, 30 females), and educational/professional background (including both industrial design and non-design fields), ensuring the reliability and generalizability of the collected user data.

Table 3. Original Evaluation Data Matrix

Sample	Satisfaction degree	Elegant	Natural	Stable	Simple	Beautiful	Soft
1	4.11	3.25	3.61	4.38	4.15	3.54	4.00
2	4.82	4.08	4.30	4.57	5.02	3.72	4.30
3	4.38	4.34	4.16	4.18	4.57	4.18	4.13
4	4.52	4.79	4.51	5.02	4.46	3.95	4.75
5	4.75	4.38	4.44	4.57	4.56	4.39	5.15
6	3.54	3.70	3.95	4.54	3.61	4.28	4.03
7	4.70	4.54	4.48	4.70	4.79	4.20	4.75
8	3.44	3.93	4.18	4.16	3.61	4.43	3.84
9	4.44	4.08	4.31	4.36	4.51	4.20	4.1
10	4.46	4.36	3.85	5.08	4.57	3.69	4.67

First, the original data matrix were converted into a normalized data matrix using the mean method based on Eqs. 1 and 2 to eliminate the influence of units. The normalized data matrix NX is shown below (with the first column as the reference sequence and columns 2-7 as the comparison sequences).

$$NX = \begin{bmatrix} 0.95 & 0.78 & 0.86 & 0.96 & 0.95 & 0.87 & 0.91 \\ 1.12 & 0.98 & 1.03 & 1.00 & 1.14 & 0.92 & 0.98 \\ 1.01 & 1.05 & 1.00 & 0.92 & 1.04 & 1.03 & 0.94 \\ 1.05 & 1.16 & 1.08 & 1.10 & 1.02 & 0.97 & 1.09 \\ 1.10 & 1.06 & 1.06 & 1.00 & 1.04 & 1.08 & 1.18 \\ 0.82 & 0.89 & 0.95 & 1.00 & 0.82 & 1.05 & 0.92 \\ 1.09 & 1.10 & 1.07 & 1.03 & 1.09 & 1.03 & 1.09 \\ 0.80 & 0.95 & 1.00 & 0.91 & 0.82 & 1.09 & 0.88 \\ 1.03 & 0.98 & 1.03 & 0.96 & 1.03 & 1.03 & 0.94 \\ 1.03 & 1.05 & 0.92 & 1.12 & 1.04 & 0.91 & 1.07 \end{bmatrix} \tag{27}$$

Then, the gray relational coefficients were calculated using Eq. 4, and the gray relational degree and subjective weights (SW) for the six CRs were computed using Eq. 5, as shown in Table 4.

Table 4. Subjective Weight Calculation Results

Number	CRs	Gray RELATIONAL DEGREE	SW
1	Elegant	0.6951	0.1610
2	Natural	0.7171	0.1661
3	Stable	0.6500	0.1506
4	Simple	0.8945	0.2072
5	Beautiful	0.6495	0.1505
6	Soft	0.7103	0.1646

Calculation of Objective Weight of Consumer Requirements Utilizing Entropy

Initially, the original data matrix was normalized using formula (7) to generate the normalized data matrix P.

$$P=\begin{bmatrix}0.00 & 0.00 & 0.24 & 0.38 & 0.00 & 0.12\\ 0.54 & 0.77 & 0.45 & 1.00 & 0.20 & 0.35\\ 0.71 & 0.61 & 0.02 & 0.68 & 0.72 & 0.22\\ 1.00 & 1.00 & 0.93 & 0.60 & 0.46 & 0.69\\ 0.73 & 0.92 & 0.45 & 0.67 & 0.96 & 1.00\\ 0.29 & 0.38 & 0.41 & 0.00 & 0.83 & 0.15\\ 0.84 & 0.97 & 0.59 & 0.84 & 0.74 & 0.69\\ 0.44 & 0.63 & 0.00 & 0.00 & 1.00 & 0.00\\ 0.54 & 0.78 & 0.22 & 0.64 & 0.74 & 0.20\\ 0.72 & 0.27 & 1.00 & 0.68 & 0.17 & 0.63\end{bmatrix} \tag{28}$$

To prevent the occurrence of zero values, a non-negative shift of 0.01 was applied to all normalized data, a process known as non-negative translation. Subsequently, the weight proportions and entropy values were computed using Eq. 9 and 10, respectively. Finally, the dispersion and normalized objective weights (OW) were determined using Eq. 11 and 12, as presented in Table 5.

Table 5. Objective Weight Calculation Results

	Elegant	Natural	Stable	Simple	Beautiful	Soft
Information Entropy	0.9365	0.9302	0.8678	0.8986	0.9093	0.8700
Dispersion Degree	0.0635	0.0698	0.1322	0.1014	0.0907	0.1300
OW	0.1081	0.1188	0.2250	0.1725	0.1544	0.2212

Calculation of Comprehensive Weight of Consumer Requirements Utilizing GT

Upon calculating the normalized SW and normalized OW, the CW of CRs were derived using GT, enabling the precise identification of the most key CRs and assisting designers in prioritizing product development.

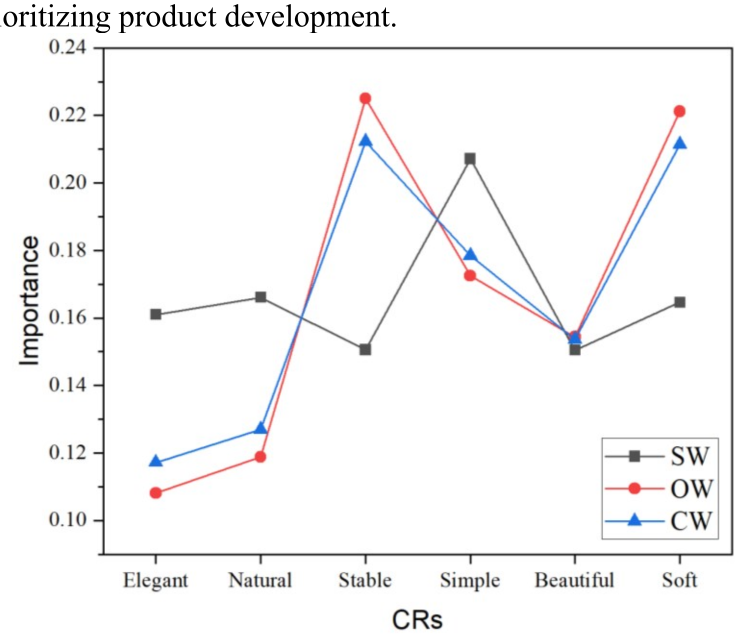


Fig. 3. Comprehensive weight calculation results

The weight coefficients for SW and OW were 0.1724 and 0.8276, respectively. The comprehensive weights for the six CRs were then computed using Eq. 18, as illustrated in Fig. 3. The resulting ranking was as follows: stable (0.2122) > soft (0.2114) > simple (0.1785) > beautiful (0.1537) > natural (0.1270) > elegant (0.1172). Among these, stable, soft, and simple emerge as the three most important CRs, and addressing these needs is likely to enhance user emotional experience and satisfaction. Consequently, these three key CRs, along with their CW, are integrated into the FQFD framework.

Generation of Novel Images of Furniture Form Utilizing DM

To train a high-quality model capable of generating diverse and richly varied forms, a larger volume of sample data is often required. High-resolution product images were collected from online shopping platforms and professional publications. Duplicate and highly similar images were then removed, resulting in a curated training set of 25 representative armchairs with distinct morphological differences. The training set was then preprocessed using Photoshop 2020, including background and shadow removal, and exported as 512×512 pixel JPG images with a white background, ensuring a high-quality dataset for training.

The LoRA model training was conducted on the Python 3.10.9 platform, with parameter settings configured using Stable Diffusion software. To train the LoRA model while minimizing GPU memory usage, the training batch size was set to 1, each image was trained for 10 iterations, the epoch was set to 10, and the learning rate was set to 1e-4. Since the training images consisted of real-world product images with intricate details, the network rank was set to 32 and the network alpha was set to 16. The runtime environment configuration and model parameter settings are shown in Table 6.

Table 6. Configuration of the Operating Environment and LoRA Parameter Settings

Operating Environment		LoRA Parameter	
Operating system	Win 11	Training batch size	1
Memory capacity	16GB	Epoch	10
Operating software	Stable diffusion 1.5	Learning rate	1e-4
Programming language	Python 3.10.9	LoRA type	Standard

The trained LoRA model was imported into Stable Diffusion to complete the image generation task. The sampler was set to Euler a, and the number of steps was set to 30, generating a total of 60 new images of bamboo armchairs. A focus group composed of experts engaged in furniture design research was invited to rigorously screen the generated images. First, images with missing forms or structural elements, as well as those of low quality or blurred resolution, were eliminated. Then, to ensure a rich diversity of design features and enhance creativity in subsequent product development, images exhibiting significant morphological differences were selected from the remaining set, while highly similar images were removed. Ultimately, 30 high-quality product images were chosen as representative samples for the deconstruction of furniture design features (Fig. 4). These new products stand out from existing offerings in the furniture market, significantly enhancing the potential for product innovation.

Fig. 4. 30 representative samples generated by the DM

An analysis and deconstruction of the design characteristics of the newly generated bamboo armchairs were conducted, identifying the most distinctive elements as morphological features. Each of these elements was encoded, and the corresponding specifications were created as standardized white-background vector images using Adobe Illustrator, as shown in Fig. 5. The bamboo armchair was categorized into six core design features: top rail, backrest, seat, stretcher, post under handrail, and foot stretcher.

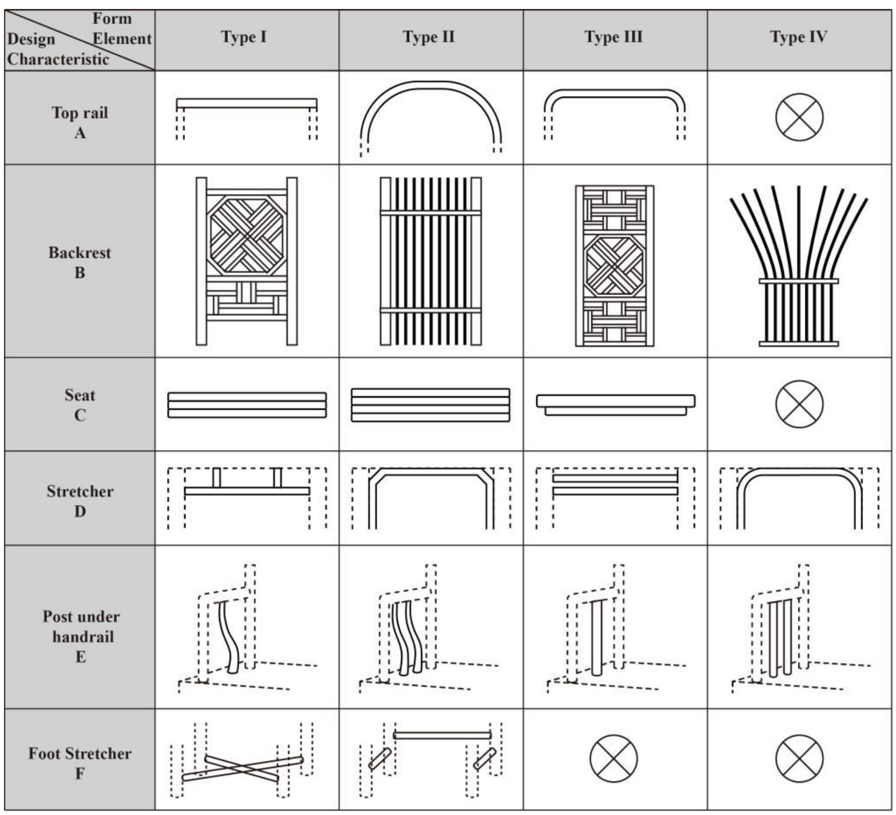
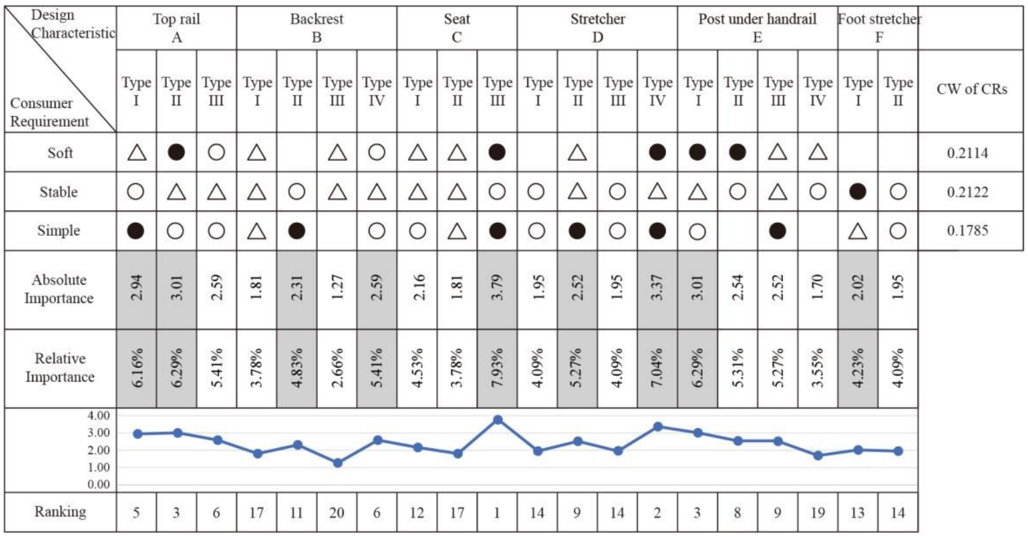


Fig. 5. DCs and form elements of bamboo armchairs.

Construction of Mapping Model Between Key Consumer Requirements and Design Characteristics Utilizing FQFD

Building on the findings from the previous stage, the key CRs identified are stable, simple, and soft. This section aims to develop a mapping model that links these key CRs with corresponding DCs. Initially, the three CRs were placed on the left side of the HoQ, while their respective CW were positioned on the right. The morphological elements, identified in the first stage, were then placed on the ceiling of the HoQ. Subsequently, the central matrix was employed to represent the strength of the relationships between the needs and features using triangular fuzzy numbers, as outlined in Table 2. The absolute and relative weights of the morphological elements were calculated using Eqs. 22 and 23, respectively, to determine the optimal combinations of design parameters that best met consumer preferences. Fig. 6 provides a visual representation of the HoQ mapping model.



Design Characteristic / Consumer Requirement	Top rail A			Backrest B				Seat C			Stretcher D				Post under handrail E				Foot stretcher F		
	Type I	Type II	Type III	Type I	Type II	Type III	Type IV	Type I	Type II	Type III	Type I	Type II	Type III	Type IV	Type I	Type II	Type III	Type IV	Type I	Type II	CW of CRs
Soft	△	●	○	△		△	○	△	△	●		△		●	●	●	△	△			0.2114
Stable	○	△	△	△	○	△	△	△	△	○	○	△	○	△	△	○	△	○	●	○	0.2122
Simple	●	○	○	△	●		○	○	△	●	○	●	○	●	○		●		△	○	0.1785
Absolute Importance	2.94	3.01	2.59	1.81	2.31	1.27	2.59	2.16	1.81	3.79	1.95	2.52	1.95	3.37	3.01	2.54	2.52	1.70	2.02	1.95	
Relative Importance	6.16%	6.29%	5.41%	3.78%	4.83%	2.66%	5.41%	4.53%	3.78%	7.93%	4.09%	5.27%	4.09%	7.04%	6.29%	5.31%	5.27%	3.55%	4.23%	4.09%	
Ranking	5	3	6	17	11	20	6	12	17	1	14	9	14	2	3	8	9	19	13	14	

Fig. 6. The mapping model of HoQ

Based on the output from the HoQ floor, it was determined that the most important morphological elements for the top rail, backrest, seat, stretcher, post under handrail, and foot stretcher are Type 2, Type 4, Type 3, Type 4, Type 1, and Type 1, respectively. In conclusion, the optimal combination of key morphological elements is identified as (A2, B4, C3, D4, E1, F1), which has the potential to enhance user satisfaction and improve the market competitiveness of bamboo furniture enterprises.

DESIGN PRACTICE

By applying FQFD, highly important morphological elements were identified among the six DCs, which can effectively guide the product development efforts of furniture companies' design departments. Based on the output of the HoQ, these elements were combined to generate four distinct preliminary furniture design concepts (Fig. 7). To determine the optimal design and validate the effectiveness of the proposed solutions, a 7-point Likert scale questionnaire was developed, incorporating the four preliminary design concepts and the three key CRs. Users were invited to evaluate each concept. The evaluation results showed that all four concepts received scores above the midpoint value of 3.5, with Scheme 1 achieving the highest overall score, identifying it as the optimal furniture design.

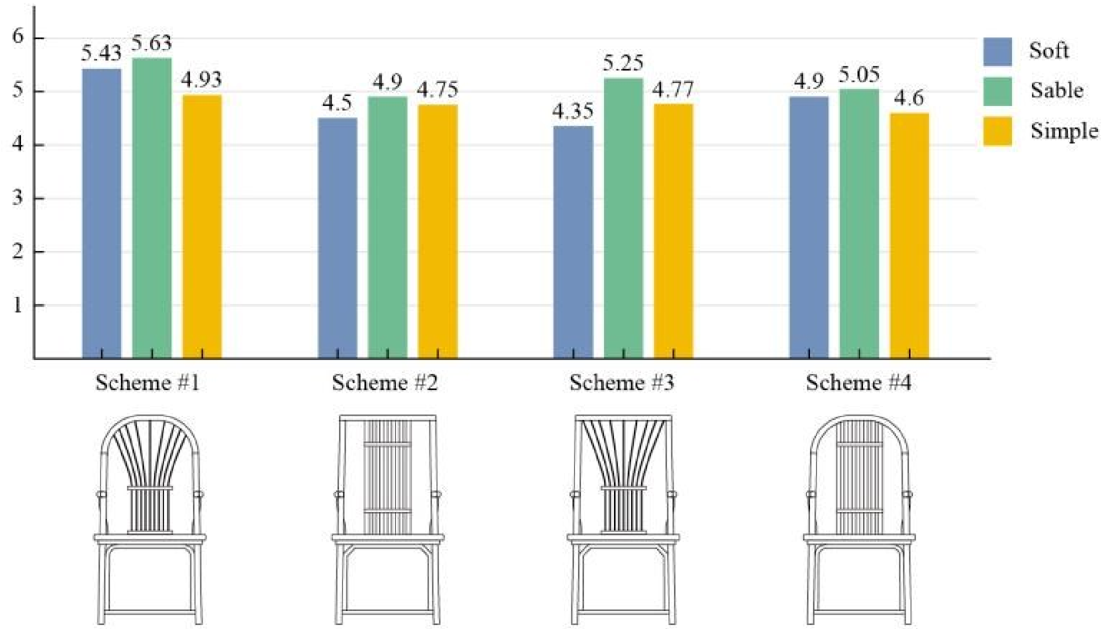


Fig. 7. Overall evaluation score of the preliminary furniture schemes

To transition the study’s findings from theoretical to practical implementation, this section employs Adobe Illustrator 2020 for vector graphics and Rhino 6 for 3D modeling to define the dimensions and intricate details of the furniture prototype. The design is then rendered using KeyShot 10 to produce realistic visual representations of the optimal furniture scheme, as illustrated in Fig. 8.

Fig. 8. Rendering model and sizes of furniture scheme

This piece of furniture is constructed entirely from biomass materials, with the primary structure made of bamboo and the seat surface woven from rattan to enhance user comfort. It reflects principles of environmental sustainability and eco-friendliness. The design is characterized by simplicity and elegance, with a focus on functionality rather than ornamentation. Additionally, components such as the armrests and headrest are designed with naturally rounded lines, resonating with the emotional preferences of modern consumers.

DISCUSSION

Bamboo furniture, recognized as a cost-effective and renewable eco-friendly option, serves two main purposes: it helps mitigate the rapid depletion of the Earth's finite resources and it caters to the growing consumer preference for healthy and sustainable consumption. Market research indicates that the current focus in bamboo furniture product development is primarily on structure and functionality, with limited exploration into how optimizing furniture form can enhance the emotional experience of consumers. Furthermore, bamboo furniture form design lacks a systematic, objective design approach and is often based on replication, imitation, or the subjective experience of designers. Sustainable form design in bamboo furniture, however, can address the increasing emotional demands of contemporary consumers, strengthen the brand appeal of bamboo furniture, and enhance market share, ultimately contributing to the development of both business competitiveness and the global ecological environment.

Therefore, this study uses the commonly encountered armchair in daily life as a case study, proposing a bamboo furniture generative design method that combines GT and AIGC, with KE as the core theoretical foundation. First, GT assisted the design team in identifying the key CRs from a wide range of potential needs. Second, the DM within AIGC technology was employed for the innovative generation of furniture images. It is important to note that, to ensure product safety, these generated images served primarily as sources of creative inspiration for designers and were not directly used for manufacturing or production. By deconstructing the design features of these newly generated furniture images, a set of innovative morphological elements was extracted. Finally, FQFD was used to identify the morphological elements most aligned with consumer needs. Based on these outputs, experienced furniture designers carried out detailed design work to ensure product safety, ultimately resulting in a finalized design proposal.

While KE provides a scientific approach for constructing mathematical relationships between user emotions and furniture features, two main limitations still need to be addressed. First, accurately and objectively identifying key CRs while minimizing the influence of expert subjectivity is essential. The identification of these key requirements is critical for the successful execution of the design and development phases. In today's user-centered design environment, refining key CRs in the early stages of design is a priority for many companies. Although techniques such as AHP and ANP can help determine the importance of various criteria, they are still expert-driven, multi-criteria decision-making methods that do not fully reflect user preferences. To address this gap, this study employs GRA and Entropy to determine the subjective and objective weights of CRs and subsequently applies GT to maximize global benefits and calculate the comprehensive weight of CRs, thus reducing information loss.

Second, it focuses on enhancing the creativity of design features to reduce homogenization issues. Currently, bamboo furniture products do not sufficiently emphasize users' emotional experiences. In the era of the experience economy, furniture companies need to enhance their market competitiveness through innovation. The DM in

AIGC technology can learn and generate new furniture forms that have not been seen in the market, producing images with high resolution and diverse characteristics.

Third, accurately translating key CRs into DCs remains a challenge. After identifying the CRs and constructing a morphological deconstruction table for the furniture, a mathematical relationship must be established between the two. Traditional KE research often uses linear regression models to establish such relationships, but methods such as multiple linear regression and QTT-1 struggle to predict complex, vague, and nonlinear emotional responses from consumers. While QFD is a straightforward and intuitive mapping method, it cannot fully capture the fuzzy, subjective thinking inherent in decision-making processes. To overcome this, the study introduces fuzzy triangular mathematical theory to enhance the functionality of traditional QFD, enabling more accurate translation of CRs into DCs.

CONCLUSIONS

The furniture industry's environmental impact is significant and cannot be overlooked. Bamboo furniture, crafted from renewable and biodegradable bamboo, offers a sustainable solution that contributes to energy conservation and emission reduction, helping mitigate the effects of greenhouse gas emissions. Additionally, as consumer awareness of sustainability grows, an increasing number of consumers are choosing bamboo furniture that meets their emotional preferences. Therefore, this study proposes a bamboo furniture generative design approach that integrates game theory (GT) with artificial intelligence-generated content (AIGC) to enhance the sensory appeal of bamboo furniture and promote sustainable development in the furniture industry. The key findings are as follows:

1. To address the limitations of using a single weighting method, GT was introduced to combine both subjective and objective weights of consumer requirements. The resulting comprehensive weights effectively assisted designers in identifying the truly critical CRs. Specifically, Grey relational analysis (GRA) and the Entropy method were used to calculate subjective and objective weights, respectively, followed by GT to determine the comprehensive weights and importance ranking of the CRs. The top three key CRs identified were stable, soft, and simple.
2. To tackle the issue of homogeneity in the bamboo furniture market, AIGC technology was employed to generate a large number of creative images, thereby enhancing product innovation. Specifically, a diffusion model (DM) was used to train and generate furniture image samples, from which DCs and morphological elements were extracted. Finally, to develop new furniture products closely aligned with the key CRs, triangular fuzzy numbers were introduced to extend the functionality of traditional QFD. A fuzzy mapping model was constructed between the three key CRs and six DCs, and optimal combinations of morphological elements were derived as design outputs.

REFERENCES CITED

Chen, D. L., and Cheng, P. P. (2020). "The style design of professional female vest based on Kansei engineering," *International Journal of Clothing Science and Technology* 32(1), 5-11. DOI: 10.1108/ijcst-07-2018-0090

Cheng, Y. F., Tor, O., Hu, L. L., Zheng, W., and Yu, Y. M. (2020). "Ergonomics of a chinese folk bamboo lounge chair," *BioResources* 15(4), 8981-8994. DOI: 10.15376/biores.15.4.8981-8994

Cohen, L. (1995). *Quality Function Deployment: How to Make QFD Work For You,* Addison-Wesley Publishing Group.

Deng, W. X., Lin, H., and Jiang, M. (2023). "Research on bamboo furniture design based on D4S (Design for Sustainability)," *Sustainability* 15(11), article 17. DOI: 10.3390/su15118832

Dhariwal, P., and Nichol, A. (2021). "Diffusion models beat GANs on image synthesis," 35th Annual Conference on Neural Information Processing Systems (NeurIPS), Dec 06-14, null, Electr Network Neural Information Processing Systems (Nips).

Dlamini, L. C., Fakudze, S., Makombe, G. G., Muse, S., and Zhu, J. G. (2022). "Bamboo as a valuable resource and its utilization in historical and modern-day China," *BioResources* 17(1), 1926-1938. DOI: 10.15376/biores.17.1.Dlamini

Fan, J. S., Yu, S. H., Yu, M. J., Chu, J. J., Tian, B. Z., Li, W. H., Wang, H., Hu, Y. K., and Chen, C. (2020). "Optimal selection of design scheme in cloud environment: A novel hybrid approach of multi-criteria decision-making based on F-ANP and F-QFD," *J. Intelligent & Fuzzy Systems* 38(3), 3371-3388. DOI: 10.3233/jifs-190630

Ho, J., Jain, A., and Abbeel, P. (2020). "Denoising diffusion probabilistic models," *Advances in Neural Information Processing Systems* 33, 6840-6851.

Jiang, Z. M. J., Ma, Y. S., and Xiong, Y. (2023). "Bio-inspired generative design for engineering products: A case study for flapping wing shape exploration," *Advanced Engineering Informatics* 58, article 11. DOI: 10.1016/j.aei.2023.102240

Kang, X. H., and Nagasawa, S. (2023). "Integrating continuous fuzzy Kano model and fuzzy quality function deployment to the sustainable design of hybrid electric vehicle," *Journal of Advanced Mechanical Design Systems and Manufacturing* 17(2), 1. DOI: 10.1299/jamdsm.2023jamdsm0019

Khoo, L. P., and Ho, N. C. (1996). "Framework of a fuzzy quality function deployment system. *International Journal of Production Research* 34(2), 299-311. DOI: 10.1080/00207549608904904

Kirgizov, U. A., and Kwak, C. (2022). "Quantification and integration of Kano's model into QFD for customer-focused product design," *Quality Technology and Quantitative Management* 19(1), 95-112. DOI: 10.1080/16843703.2021.1992070

Lai, C. G., Chen, X. H., Chen, X. Y., Wang, Z. L., Wu, X. S., and Zhao, S. W. (2015). "A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory," *Natural Hazards* **77**(2), 1243-1259.

Li, X. J., 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), article 19.

Liu, Z. M., Chen, X. H., and Liang, X. A. (2024). "Growable design of passenger vehicle interior space based on FAHP and FQFD," *Plos One* 19(6), 30. DOI: 10.1371/journal.pone.0303233

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

Norman, D. (2007). *Emotional Design: Why We Love (or Hate) Everyday Things*, Basic books.

Qiu, K., Su, J. N., Zhang, S. T., and Yang, W. J. (2022). "Research on product target image cognition based on complex network theory and game theory," *Journal of Advanced Mechanical Design Systems and Manufacturing* 16(6), article 17. DOI: 10.1299/jamdsm.2022jamdsm0064

Sharma, B., and van der Vegte, A. (2020). "Engineered bamboo for structural applications," in: *Nonconventional and Vernacular Construction Materials* pp. 597-623.

Shieh, M. D., Li, Y. F., and Yang, C. C. (2018). "Comparison of multi-objective evolutionary algorithms in hybrid Kansei engineering system for product form design," *Advanced Engineering Informatics* 36, 31-42. DOI: 10.1016/j.aei.2018.02.002

Smith, S., and Fu, S. H. 2011. "The relationships between automobile head-up display presentation images and drivers' Kansei," *Displays* 32(2), 58-68. DOI: 10.1016/j.displa.2010.12.001

Sofiana, Y., Wahidiyat, M., and Sylvia Caroline, O. (2018). "Bamboo as sustainable material for furniture design in disaster and remote areas in Indonesia," *IOP Conference Series: Earth and Environmental Science*, article 012150. DOI: 10.1088/1755-1315/126/1/012150

Tang, W. Y., Xiang, Z. R., Yu, S. L., Zhi, J. Y., and Yang, Z. (2025). "PSR-GAN: A product concept sketch rendering method based on generative adversarial network and colour tags," *Journal of Engineering Design* 23, article 2450760. DOI: 10.1080/09544828.2025.2450760

Wang, N., Kang, X., Wang, Q., and Shi, C. (2023). "Using grey-quality function deployment to construct an aesthetic product design matrix," *Concurrent Engineering* 31(1-2), 49-63. DOI: 10.1177/1063293x221142289

Wang, T. X., and Yang, L. (2023). "Combining GRA with a Fuzzy QFD model for the new product design and development of Wickerwork lamps," *Sustainability* 15(5), article 21. DOI: 10.3390/su15054208

Yang, C. X., Liu, F., and Ye, J. N. (2023a). "A product form design method integrating Kansei engineering and diffusion model," *Advanced Engineering Informatics* 57(14), article 102058. DOI: 10.1016/j.aei.2023.102058

Yang, Y. Q., Wang, S. Q., Dulaimi, M., and Low, S. P. (2003b). "A fuzzy quality function deployment system for buildable design decision-makings," *Automation in Construction* 12(4), 381-393. DOI: 10.1016/s0926-5805(03)00002-5

Zheng, Y. W., and Zhu, J. G. (2021). "The application of bamboo weaving in modern furniture," *BioResources* 16(3), 5024-5035. DOI: 10.15376/biores.16.3.5024-5035

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