# Creative Design and Evaluation of New Chinese-Style Furniture Combining Stable Diffusion with CRITIC–VIKOR Method

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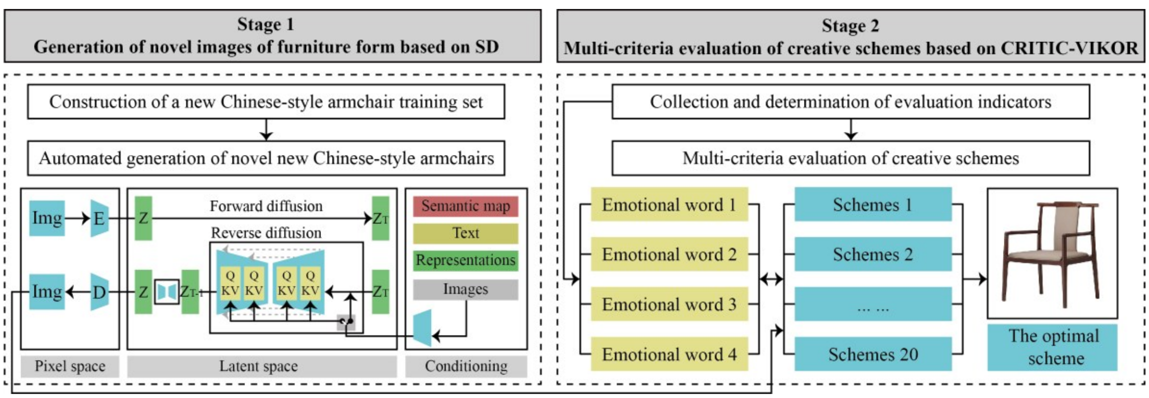
## GRAPHICAL ABSTRACT



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Traditional furniture design relies heavily on designers' prior knowledge and limited individual capacity, which often results in insufficient innovation capability and low product development efficiency. To overcome these limitations, this study introduces advanced Artificial Intelligence Generated Content (AIGC) technology and proposes an integrated creative design and evaluation framework for new Chinese-style furniture that combines Stable Diffusion (SD) with the CRITIC–VIKOR method. The proposed method aims to enhance research and development efficiency and creativity while enabling a comprehensive assessment of generated furniture design alternatives. Specifically, the SD model within the AIGC technology is employed to train and generate innovative furniture design images. After identifying affective words that represents user needs, the CRITIC–VIKOR method is applied to calculate the objective weights of user needs and to conduct a multi-criteria evaluation of the creative schemes, thereby determining the optimal scheme. The proposed method effectively integrates the strengths of generative technologies and quantitative decision-making approaches. It facilitates the rapid generation of diverse creative concepts while systematically selecting the optimal scheme that best satisfies user requirements, thereby promoting the development of the furniture industry and fostering the inheritance and innovative advancement of traditional culture.

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*Keywords: Creative design and evaluation; New Chinese-style furniture; Stable diffusion; CRITIC–VIKOR method; AI–generated content (AIGC)*

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## INTRODUCTION

New Chinese-style furniture is a design style that emerged in China in the early 21st century and has gradually matured over time. It inherits the refined craftsmanship and aesthetic principles of traditional Ming and Qing dynasty furniture while fully incorporating contemporary user demands, thereby representing a new category of household products that integrates traditional cultural elements with modern technologies. New Chinese-style furniture effectively continues the ecological and environmentally friendly characteristics of traditional Ming and Qing furniture. As wooden furniture constructed with mortise-and-tenon joinery, it is generally more sustainable and low-carbon than plastic or metal furniture. To a certain extent, it helps mitigate ecological issues such as the depletion of limited natural resources and environmental pollution. Wooden furniture occupies an extremely important position within the furniture industry (Lin *et al*. 2019). With the acceleration of urbanization in China, the upgrading of consumer demand,

and the rise of cultural confidence, the market share of new Chinese-style furniture in the domestic home furnishing market has increased steadily year by year. It has become an important component of China's wooden furniture industry and has gained widespread recognition among consumers.

In recent years, new Chinese-style furniture has been increasingly favored by Chinese consumers, particularly younger generations, as it aligns with contemporary aesthetic preferences while embodying the advantages of environmental sustainability and health consciousness. However, from the perspective of research and development (R&D) of products, several limitations remain that require urgent improvement. In the current era of Industry 4.0, many furniture enterprises still adhere to traditional design paradigms, relying heavily on designers' limited energy and subjective experience. Design schemes often undergo repetitive and complex revisions, while drafting and modeling tasks consume a substantial proportion of development time. Consequently, designers are able to devote only limited effort to creative conceptual exploration, leading to slow product iteration and relatively low R&D efficiency. In essence, new Chinese-style furniture inherits the mature structural systems and craftsmanship of Ming and Qing dynasty furniture and has evolved over many years. As a result, it is difficult for different enterprises to achieve significant differentiation in terms of structure and manufacturing techniques. Form, as an explicit and perceptible product attribute, directly influences consumers' first impressions (Norman 2007). Therefore, morphological innovation in design is of critical importance and can serve as a strategic instrument for enterprises to gain competitive advantage in the marketplace (Bloch 1995).

With the rapid advancement of artificial intelligence technologies, AIGC has driven progress across numerous industries by learning from existing datasets to produce novel content. The core technologies underlying AIGC primarily include Generative Adversarial Networks (GANs) (Goodfellow *et al*. 2014), autoregressive generative models (Larochelle and Murray 2011), and diffusion models (Ho 2020). GANs were once the dominant paradigm in image generation; however, they suffer from issues such as training instability, limited controllability, and moderate image quality, particularly due to their high dependence on large-scale image datasets. Autoregressive generative models are more suitable for natural language processing (NLP) tasks rather than image generation. In contrast, diffusion models have emerged as the most prevalent generative paradigm in recent years, owing to their superior generation quality, strong controllability, high diversity, and relatively lower requirements for training data scale. AIGC technologies represented by diffusion models have recently been introduced into the field of industrial design, giving rise to a new research paradigm of intelligent generative design. Technological advancements have enabled the continuous emergence of creative concepts, effectively addressing inherent challenges such as design homogeneity and low efficiency. For example, Yang *et al.* (2023) employed diffusion models to train and generate novel product images and subsequently constructed a predictive model between product form and Kansei words using support vector regression. Kang and Wang (2025) utilized the Stable Diffusion model to generate a large number of wood-carved window patterns, thereby significantly enhancing the diversity of cultural and creative design solutions. These studies demonstrate the considerable potential of AIGC technologies in industrial design applications. However, there has been a need for studies considering the application of technologies to the design of new Chinese-style furniture. Therefore, this study adopts Stable Diffusion (SD) (Rombach *et al*. 2022), a representative diffusion model, to train and generate images of new Chinese-style furniture. Stable Diffusion is capable of producing high-resolution and diverse images within seconds on consumer-grade GPUs. It also offers strong semantic controllability and scalability, thereby assisting furniture designers in rapidly generating a large volume of creative concepts.

However, AIGC technologies such as Stable Diffusion do not inherently possess the capability to evaluate image quality. Given the high degree of diversity and randomness in the generated outputs, it remains difficult to determine the optimal product scheme for market launch solely through generative techniques. To address this limitation, Multi-Criteria Decision Analysis (MCDA) provides a reliable quantitative evaluation framework, enabling comprehensive assessment across multiple criteria and yielding an optimal decision outcome. Common subjective decision-making methods, such as the Analytic Hierarchy Process (AHP) (Saaty 2008), rely excessively on the subjective judgments of a limited number of experts. In contrast, objective weighting methods such as the entropy weight method (Zhu *et al*. 2020) depend entirely on data quality and are sensitive to outliers. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Lai *et al*. 1994) is highly sensitive to indicator normalization and weight assignment. The CRITIC–VIKOR method (Saraji *et al*. 2023) represents a hybrid decision-making approach that integrates the advantages of objective weighting and compromise ranking. Compared with the entropy weight method, CRITIC offers a key advantage in that it considers not only the variability of individual indicators but also the correlations among them, thereby generating more comprehensive, robust, and interpretable objective weights. Accordingly, this study integrates the strengths of Stable Diffusion and the CRITIC–VIKOR method to conduct a comprehensive evaluation of generated new Chinese-style furniture images, ultimately identifying the optimal scheme that is both innovative and aligned with users' affective needs.

This study aims to promote efficient collaboration between AIGC technology and designers by emphasizing the role of AI as a supportive tool rather than a complete replacement for human creativity and expertise. In addition, the study integrates multidisciplinary methods to overcome the limitations of a single approach and establish an efficient and scientific pathway for furniture design. Overall, this study makes the following three main contributions: (1) An integrated creative design and evaluation framework for new Chinese-style furniture was developed by combining Stable Diffusion (SD) with the CRITIC–VIKOR method. This framework fully integrates the creative capability of AIGC technology with the quantitative evaluation ability of MCDA methods, enabling the generated furniture designs to possess both creativity and emotional value. The proposed method also addresses the emotional needs of contemporary users and supports the productive preservation of traditional Chinese culture. (2) Rapid generation of creative new Chinese-style furniture designs was achieved. The combination of SD and LoRA models can capture and learn the form characteristics of new Chinese-style furniture and generate innovative furniture images that are not currently available on the market. This approach improves design efficiency to a certain extent and helps reduce designers' workload. (3) Emotional evaluation of creative design solutions was conducted. The CRITIC–VIKOR method was used to comprehensively evaluate the generated furniture schemes, allowing more scientific and systematic selection of solutions that better match contemporary user preferences and enhance product market competitiveness.

The overall structure of this paper is organized as follows. First, a literature review includes the research objective and relevant methodologies to clarify the current state of the field. Secondly, the methods section presents the research framework and provides a detailed description of the proposed methods. Third, the case study and results validates the feasibility of the proposed approach through a practical design case of a new Chinese-style armchair, followed by an extended discussion, and conclusions.

## LITERATURE REVIEW

### New Chinese-Style Furniture Form

In recent years, research on the form of new Chinese-style furniture has gradually attracted scholarly attention. However, existing studies have primarily focused on the relationship between furniture attractiveness and users' affective preferences, with relatively few reports addressing innovative form design of new Chinese-style furniture. Particularly in the current era of artificial intelligence, emerging AI technologies offer significant potential to empower innovation in furniture design. For instance, Cui *et al.* (2025) employed eye-tracking technology and user experience surveys to evaluate the relationship between consumer preferences and the visual attractiveness of furniture, revealing that consumers adopt different cognitive processing strategies when interacting with various furniture attributes. Wan *et al.* (2018) utilized eye-tracking analysis to investigate contemporary users' preferences for traditional Chinese furniture and new Chinese-style furniture, finding that participants exhibited greater interest in the latter.

### Product Image Generation

Deep generative models constitute a fundamental component of deep learning and serve as the core technological foundation for product image generation. By learning the underlying probability distribution of data, deep generative models enable the sampling of new data instances from that distribution, encompassing multiple modalities such as images, text, and audio. Mainstream deep generative models include autoregressive models, Generative Adversarial Networks (GANs), Variational Auto-Encoders (VAEs), and diffusion models (DMs). The emergence of these algorithms has substantially enhanced innovation and efficiency within the field of product design.

Diffusion models (DMs) construct a forward process by progressively adding noise to data and subsequently learn a reverse process to remove the noise and reconstruct the data (Ho 2020). This approach has demonstrated outstanding performance in image generation tasks and is capable of producing high-quality visual outputs. In recent years, diffusion models have gradually surpassed other deep generative paradigms and have become one of the principal algorithms for creative product image generation. For example, Kang *et al.* (2025) employed DMs to learn and generate novel Miao batik patterns, which were subsequently integrated into handbag design. Liu *et al*. (2025), aiming to enhance design inspiration for bamboo furniture, utilized DMs to generate a variety of new bamboo furniture images and then applied Quality Function Deployment to establish a mathematical relationship between new furniture forms and user requirements. Yang *et al.* (2023) generated thermometer images using DMs and subsequently constructed a predictive model based on Support Vector Regression, thereby achieving both innovative and affective product design. These studies demonstrate the considerable potential of diffusion model technology in the domain of creative product image generation. Building upon this foundation, the present study introduces Stable Diffusion, a representative diffusion model, into the design of new Chinese-style furniture. While preserving essential design elements of existing furniture, the proposed approach generates novel products enriched with enhanced innovative features.

### Product Multi-Criteria Evaluation

The primary advantages of product image generation lie in its creativity and productivity; however, deep generative models themselves lack evaluation capabilities. Multi-criteria product evaluation refers to methods that employ multiple indicators to conduct comprehensive decision-making and ranking among alternative product schemes. Common multi-criteria evaluation methods include the AHP, TOPSIS, and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). Among these, AHP relies heavily on the prior knowledge of a limited number of experts, and conclusions derived from different expert groups tend to exhibit strong subjectivity. The TOPSIS method identifies the optimal solution as the one closest to the positive ideal solution and farthest from the negative ideal solution, focusing primarily on relative distance to the ideal point. In contrast, the VIKOR method evaluates alternatives by comprehensively considering group utility, individual regret, and overall compromise, thereby yielding more reliable results. Consequently, it has been widely introduced into product optimization and decision-making research. For example, Qu *et al.* (2025) applied the VIKOR method to select the optimal solution from five air purifier design schemes, providing robust decision support for air purifier development. Wang *et al*. (2017) incorporated the VIKOR method into affective product design to prioritize different product combinations and identify attractive solutions. Despite its advantages, the VIKOR method does not inherently provide a mechanism for determining indicator weights and thus cannot independently assess the relative importance of evaluation criteria. To address this limitation, the present study introduces the CRITIC method to objectively assign weights to evaluation indicators. The resulting CRITIC–VIKOR framework integrates data-driven objective weighting with a compromise ranking mechanism. This approach not only overcomes the dependence on subjective weight assignment in traditional VIKOR applications but also enhances discrimination and stability in evaluation by accounting for inter-criteria conflict. Therefore, it demonstrates particular advantages in comprehensive evaluation scenarios characterized by multiple conflicting and highly correlated criteria.

## METHODS

The research methodology is divided into two main stages (Fig. 1).

Stage 1 focuses on furniture form creative image generation based on SD. First, a large number of images of new Chinese-style furniture are collected, from which high-resolution, diverse, and representative images are selected to construct the training dataset. Subsequently, a LoRA-enhanced SD model is employed for model training and image generation, and 20 high-quality creative design schemes are selected from the generated outputs. Stage 2 involves multi-criteria evaluation of the creative schemes based on the CRITIC–VIKOR method. Initially, affective words representing user needs is collected and screened. A seven-point Likert scale questionnaire is then administered to gather user evaluation data. The CRITIC method is applied to calculate the objective weights of the affective indicators, and finally, the VIKOR method is employed to rank the alternatives according to their overall performance, thereby identifying the optimal creative scheme.

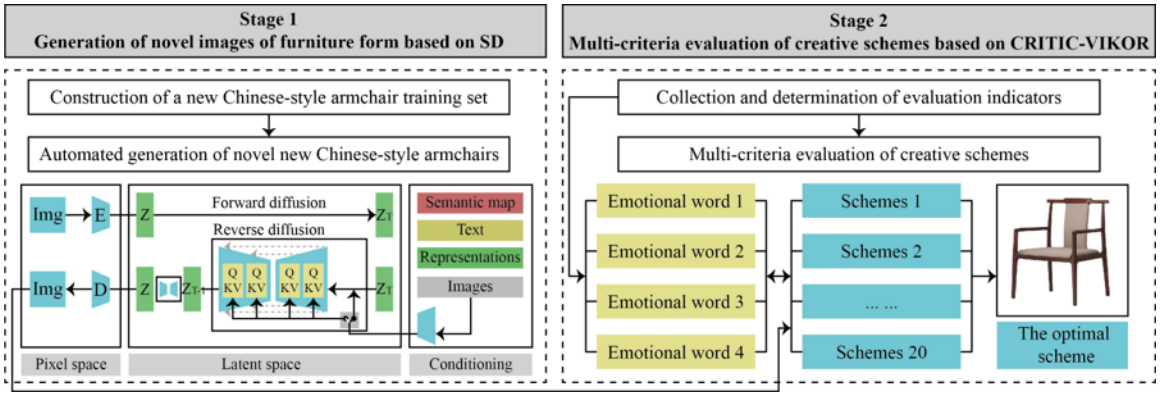


**Fig. 1.** The method framework of creative design and evaluation of new Chinese-style furniture

## Stable Diffusion

In diffusion models, the diffusion process is performed in the latent space. Initially, the input image is encoded into low-dimensional latent representations through an encoder. Once the images of new Chinese-style furniture are transformed into latent data, both the forward diffusion process and the reverse diffusion process are conducted within the latent space. The forward diffusion process involves progressively adding noise to the latent representations, whereas the reverse diffusion process removes the noise from the latent variables. Finally, the denoised latent representations are decoded by a decoder to generate new high-quality images.

The forward diffusion process gradually injects Gaussian noise into the data over a total of $T$ time steps. As described in Eq. 1, Gaussian noise is incrementally added at each time step $t$. After completing all $T$ steps, the original data are fully transformed into pure noise,

$$q(x_t|x_{t-1}) = N(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I) \tag{1}$$

where $t$ denotes the time step, and $x_t$ represents the data sample at step $t$, evolving from $x_0$ to $x_T$. The parameter $\beta_t$ is the noise variance coefficient, whose value lies within the interval [0, 1], and $I$ denotes the identity matrix.

The reverse diffusion process can be described by Eq. 2.

$$q(x_{t-1}|x_t) = N(x_{t-1}; \mu_t(x_t, x_0), \beta_t I) \tag{2}$$

Unlike the forward process, directly reversing the noise through $q(x_{t-1}|x_t)$ is intractable. To enable new image generation, a tractable neural network $p_\theta(x_{t-1}|x_t)$ is introduced to perform the denoising operation and ultimately reconstruct x0. This neural network can be expressed as shown in Eq. 3,

$$p_\theta(x_{t-1}|x_t) = N(x_{t-1}; \mu_\theta(x_t, t), \sum_\theta(x_t, t)) \tag{3}$$

where $\mu_e$ denotes the mean parameterized by the neural network and $\sum_e$ represents the variance parameterized by the neural network.

## CRITIC

First, the alternative schemes and evaluation criteria are determined to construct the original evaluation data matrix $X$, as shown in Eq. 4,

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{4}$$

where $n$ denotes the number of alternative schemes and $m$ represents the number of evaluation criteria.

To eliminate the influence of different measurement scales, the original matrix $X$ must be normalized. Positive and negative criteria are processed using Eq. 5 and 6, respectively. Since all evaluation criteria in this case study are positive (*i.e.*, higher user evaluation scores indicate better performance), Eq. 5 is adopted.

$$x_{ij}^{'} = \frac{x_j - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

$$x_{ij}^{'} = \frac{x_{\max} - x_j}{x_{\max} - x_{\min}} \tag{6}$$

Subsequently, the variability and conflict of the normalized criteria are calculated. Variability reflects the degree of dispersion of each criterion and is measured by the standard deviation. A larger standard deviation indicates greater discriminatory power and thus a higher weight for the corresponding criterion, as shown in Eqs. 7 and 8.

$$\bar{x}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} \tag{7}$$

$$S_j = \sqrt{\frac{\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2}{n-1}} \tag{8}$$

where $S_j$ denotes the standard deviation of the j-th evaluation criterion.

Conflict is assessed using correlation coefficients to evaluate the degree of interdependence among criteria. A lower correlation implies greater conflict, indicating less redundancy of information between criteria and therefore a higher weight, as expressed in Eq. 9.

$$R_j = \sum_{j=1}^{m} (1 - r_{ij}) \tag{9}$$

where $r_{ij}$ represents the correlation coefficient between criteria $i$ and $j$.

After determining variability and conflict, the amount of information for each criterion is calculated using Eq. 10. A larger information value indicates a greater contribution of the corresponding evaluation criterion,

$$C_j = S_j \times R_j \tag{10}$$

where $C_j$ denotes the information content.

Finally, the objective weights are obtained using Eq. 11.

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{11}$$

## VIKOR

First, the original evaluation data matrix $X$ is normalized using Eq. 12.

$$x_{ij}^{'} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}^2} \tag{12}$$

Subsequently, the group utility value and individual regret value are determined. Specifically, the maximum and minimum values of each column in the normalized matrix are identified, as shown in Eq. 13.

$$\begin{cases} x_i^+ = \max\limits_{1 \le i \le n} x_{ij}^{'} \\ x_i^- = \min\limits_{1 \le i \le n} x_{ij}^{'} \end{cases} \tag{13}$$

The group utility value is then calculated using Eq. 14, and the individual regret value is computed using Eq. 15.

$$S_i = \sum_{j=1}^{m} w_j (x_i^+ - x_{ij}^{'}) / (x_i^+ - x_i^-) \tag{14}$$

$$R_i = \max_{1 \le j \le m} [w_j (x_i^+ - x_{ij}^{'}) / (x_i^+ - x_i^-)] \tag{15}$$

Based on these results, the compromise decision index is calculated according to Eq. 16. All alternative schemes are subsequently ranked according to the computed compromise decision values, and the scheme with the smallest compromise index is identified as the optimal solution,

$$Q_i = \frac{v(S_i - S^-)}{S^+ - S^-} + \frac{(1-v)(R_i - R^-)}{R^+ - R^-} \tag{16}$$

where $v$ denotes the decision-making mechanism coefficient. When $v$ = 0.5, it indicates that achieving maximum group utility and minimizing individual regret are considered equally important. In general, $v$ is set to 0.5.

## The KJ Method

The KJ method, also known as the Affinity Diagram, was developed by Professor Jiro Kawakita at the Tokyo Institute of Technology in Japan. It is a card-based information classification technique primarily used to organize and structure fragmented and disordered information. It is widely applied in business activities and is commonly used in furniture design research to organize and categorize user requirements.

The method generally consists of the following steps: (1) defining the research problem and target; (2) collecting relevant information through direct observation and brainstorming; (3) converting the collected information into cards; (4) grouping the cards based on similarity judgments; and (5) summarizing and interpreting the results.

## CASE STUDY

### Construction of the Training Dataset for New Chinese-style Armchairs

To comprehensively capture the diverse morphological characteristics of new Chinese-style armchairs, this study first employed a combination of manual retrieval and web crawling techniques to collect a large number of product images from various online e-commerce platforms. To ensure the quality of the training dataset, professional furniture designers conducted a rigorous screening process to eliminate low-quality samples characterized by blurriness or indistinct stylistic features. In addition, only images presented in a three-quarter perspective view were retained, as this viewpoint most effectively showcases the structural and morphological features of the furniture. After screening, 50 high-resolution images were selected for inclusion in the dataset.

Preliminary investigation showed that most new Chinese-style furniture manufacturers are small and medium-sized enterprises. Compared with large-scale training models such as GANs, SD has the advantage of supporting few-shot learning. It is therefore particularly suitable for small and medium-sized furniture enterprises and can effectively reduce initial investment costs. Accordingly, a training set of 50 high-quality images is sufficient and reasonable. Subsequently, designers used Adobe Photoshop to perform standardized preprocessing on the selected images. Backgrounds, shadows, and other visual distractions were removed, preserving only the main body of the furniture. Finally, all images were uniformly resized to 512 × 512 pixels and saved in JPG format to facilitate more effective recognition and learning by the artificial intelligence model.

### Automated Generation of Creative New Chinese-style Armchairs

Upon completion of the training dataset construction, LoRA model training was initiated. Prior to formal training, a series of parameters were appropriately configured, including the learning rate, number of epochs, and optimizer settings. First, the pre-trained model selected is Stable Diffusion-v-1-5. This model has relatively low GPU requirements and enables lightweight and high-speed LoRA training. It is capable of handling various tasks, including artistic illustration, realistic portraits, anime, product design, scene generation, and concept art. It also supports stable training at a resolution of 512 × 512 pixels. The model is saved in the safetensors format. Regarding hyperparameter configuration, the number of epochs was set to six. To enable the LoRA model to sufficiently learn the image features, the training process was repeated 15 times. The learning rate was maintained at the default value (0.0001), and the learning rate scheduler was set to the default cosine strategy. The maximum resolution was aligned with the training dataset specification and set to 512 × 512 pixels. For cartoon-style datasets, smaller values of network rank and network alpha are generally sufficient due to the lack of fine-grained details. However, this study involved high-resolution realistic images characterized by richer details and more complex forms. Therefore, the parameter values were increased appropriately, with network rank set to 64 and network alpha set to 32. The entire training process was conducted in a Python environment on a Windows 11 operating system with 16 GB of RAM, ensuring sufficient computational capacity for the image training task. The total training time was 27 minutes and 27 seconds.

After training, the LoRA model in safetensors format was imported into Stable Diffusion for image generation. The text-to-image function was selected, with the sampling method set to Euler a and the number of inference steps set to 25. The batch size was limited to one image per generation to reduce GPU memory consumption. The output image dimensions were set to 512 × 512 pixels, consistent with the training dataset. Prompt engineering was applied to guide the generation process. Positive prompts included terms such as “armchair”, “full body”, “white background”, “simple background”, “no humans”, “4K”, “masterpiece”, and “high quality”, while negative prompts included “blur”, “ugly”, “bad proportions”, and “error”.

Stable Diffusion enhanced with LoRA generated approximately 200 creative new Chinese-style armchair images. To simplify the subsequent comprehensive evaluation and reduce the burden on users, this study invited an expert panel consisting of five designers and researchers in furniture design or industrial design. Each expert had at least five years of professional experience. First, images with obvious structural issues or incomplete forms were removed. Then, the remaining images were compared with those in the training set, and those with high morphological similarity were excluded. Finally, the expert panel reached a consensus and selected 20 representative designs with clearly distinct forms. These selected designs exhibit novel furniture concepts that have not yet appeared in the market.

As illustrated in Fig. 2, the selected images demonstrate clear and delicate textures, as well as diversified styles and materials, achieving a high degree of visual realism. This process not only substantially improves the efficiency of furniture designers but also provides reliable sources of design inspiration. In the subsequent section, these schemes will undergo multi-criteria evaluation to determine the optimal solution. In addition, a careful comparison between the generated images and the training set reveals that the generated designs both retain and integrate certain morphological characteristics of the training data, while also introducing entirely new forms that do not appear in any training samples. This ensures that the generated furniture images preserve the genetic features of the training set, while also extending them with novel elements. As a result, they achieve a balanced integration of inheritance and innovation.


**Fig. 2.** Selected high-quality creative schemes

## Collection and Determination of Evaluation Criteria

User-Centered Design (UCD) emphasizes placing user experience at the core of design decision-making. Aligning business objectives with authentic user needs is a prerequisite for effective design development. In product form design, affective word serves as a critical medium through which consumers articulate their expectations and perceptions of product morphology. Therefore, to design new Chinese-style furniture that aligns with user needs, affective word was adopted as the set of evaluation criteria in this study. Representative affective word reflecting user demands was collected through both online and offline channels. The online approach involved web crawling and manual retrieval of authentic user reviews from e-commerce platforms. The offline approach consisted of consulting relevant professional literature and extracting descriptive passages pertaining to the form characteristics of new Chinese-style furniture. After compiling the original textual data, affective terms were extracted. Negative affective words were removed, as they reflect undesirable product attributes, while positive affective vocabulary was retained. Subsequently, a focus group composed of several experts was invited to classify and screen the extracted terms using the card sorting method. Semantically similar words were grouped into categories, and one representative term was retained for each category. Through this process, four representative affective words were ultimately identified: Minimalist, Comfortable, Graceful, and Rounded.

## Multi-criteria Decision of Creative Schemes

The four selected representative emotional vocabulary items and the 20 innovative design solutions were used to construct a 7-point Likert scale questionnaire. In this scale, 1 indicates “strongly inconsistent,” 2 “inconsistent,” 3 “somewhat inconsistent,” 4 “neutral,” 5 “somewhat consistent,” 6 “consistent,” and 7 “strongly consistent.” The questionnaire was distributed to 81 users for evaluation. All respondents had prior experience with new Chinese-style furniture; otherwise, they were not eligible to participate in this survey. The gender distribution was balanced, including 41 males and 40 females. The age distribution was broad, with 29 respondents aged 18 to 30, 39 aged 31 to 40, 3 aged 41 to 50, 8 aged 51 to 60, and 2 aged 60 and above. The questionnaire was structured into two sections. Section 1 collected demographic information, while Section 2 contained the formal evaluation of the 20 representative design solutions. The survey was administered and collected online. All participants were fully informed and participated voluntarily. All questionnaires passed the quality control checks. The resulting evaluation data matrix is shown in Table 1. Before calculating the objective weights of the four evaluation criteria, the data were normalized to eliminate dimensional differences. Subsequently, the variability and conflict of the four criteria were computed using Eqs. 7 to 9. Finally, the information content of each criterion was obtained using Eq. 10. A higher information value corresponds to a higher objective weight. The resulting importance ranking is as follows (Table 2): Minimalist (27.0%) > Rounded (25.0%) > Graceful (24.8%) > Comfortable (23.2%).

**Table 1.** Evaluation Data Matrix

| Creative scheme number | Representative affective words | | | |
|---|---|---|---|---|
| | Minimalist | Comfortable | Graceful | Rounded |
| No. 1 | 5.19 | 5.05 | 4.72 | 4.80 |
| No. 2 | 4.86 | 5.19 | 4.74 | 5.17 |
| No. 3 | 5.41 | 5.16 | 5.25 | 5.11 |
| No. 4 | 4.84 | 4.88 | 4.75 | 4.78 |
| No. 5 | 5.36 | 5.11 | 4.72 | 4.99 |
| No. 6 | 4.95 | 4.8 | 4.91 | 4.91 |
| No. 7 | 5.58 | 5.22 | 4.79 | 4.53 |
| No. 8 | 4.91 | 4.79 | 4.52 | 5.73 |
| No. 9 | 4.65 | 5.40 | 4.86 | 4.69 |
| No. 10 | 4.79 | 4.79 | 4.78 | 5.38 |
| No. 11 | 4.51 | 4.95 | 5.25 | 4.83 |
| No. 12 | 5.47 | 5.26 | 5.00 | 4.41 |
| No. 13 | 4.88 | 4.94 | 4.84 | 4.85 |
| No. 14 | 4.89 | 4.79 | 5.01 | 4.70 |
| No. 15 | 5.47 | 4.53 | 4.63 | 4.64 |
| No. 16 | 4.90 | 4.86 | 4.53 | 4.68 |
| No. 17 | 4.85 | 5.27 | 4.68 | 4.79 |
| No. 18 | 4.69 | 4.89 | 4.93 | 4.91 |
| No. 19 | 4.89 | 4.70 | 4.90 | 4.60 |
| No. 20 | 4.78 | 4.51 | 4.79 | 4.91 |

**Table 2.** Objective Weight Calculation Result

| Evaluation criteria | Variability | Conflict | Information content | Objective weight |
|---|---|---|---|---|
| Minimalist | 0.287 | 3.152 | 0.904 | 27.05% |
| Comfortable | 0.278 | 2.789 | 0.774 | 23.17% |
| Graceful | 0.269 | 3.084 | 0.829 | 24.80% |
| Rounded | 0.230 | 3.637 | 0.835 | 24.98% |

The objective weights obtained above were incorporated into the VIKOR method for subsequent computation. A multi-criteria evaluation was conducted with respect to the four evaluation criteria across 20 alternative design schemes. After normalization, Eqs. 14 and 15 were applied to calculate the group utility values (S values) and individual regret values (*R* values) for the 20 creative samples, respectively. Subsequently, the compromise values (*Q* values) were derived by integrating the results of the *S* and *R* measures. The *Q* value reflects the degree of closeness between each alternative and the ideal solution; a smaller *Q* value indicates superior overall performance. Based on the ranking of *Q* values, the alternatives were ordered accordingly, and Creative Scheme No. 3 was identified as the optimal solution, demonstrating strong comprehensive performance across all four evaluation criteria (Table 3).

**Table 3.** The Calculation and Ranking Results of VIKOR

| Creative scheme number | Group utility values ($S_i$) | Individual regret values ($R_i$) | Compromise values ($Q_i$) | Ranking |
|---|---|---|---|---|
| No. 1 | 0.5436 | 0.1810 | 0.5064 | 5 |
| No. 2 | 0.5154 | 0.1812 | 0.4807 | 4 |
| No. 3 | 0.2232 | 0.1174 | 0.0000 | 1 |
| No. 4 | 0.6695 | 0.1866 | 0.6420 | 12 |
| No. 5 | 0.4542 | 0.1810 | 0.4230 | 2 |
| No. 6 | 0.5863 | 0.1596 | 0.4761 | 3 |
| No. 7 | 0.4299 | 0.2273 | 0.5515 | 7 |
| No. 8 | 0.5783 | 0.2480 | 0.7574 | 16 |
| No. 9 | 0.5641 | 0.2353 | 0.7028 | 13 |
| No. 10 | 0.5862 | 0.2002 | 0.6085 | 10 |
| No. 11 | 0.5585 | 0.2705 | 0.8124 | 18 |
| No. 12 | 0.3982 | 0.2498 | 0.5955 | 9 |
| No. 13 | 0.6026 | 0.1758 | 0.5443 | 6 |
| No. 14 | 0.6097 | 0.1948 | 0.6130 | 11 |
| No. 15 | 0.6723 | 0.2271 | 0.7765 | 17 |
| No. 16 | 0.7598 | 0.2455 | 0.9184 | 20 |
| No. 17 | 0.5895 | 0.1934 | 0.5896 | 8 |
| No. 18 | 0.6206 | 0.2245 | 0.7201 | 14 |
| No. 19 | 0.6900 | 0.2148 | 0.7531 | 15 |
| No. 20 | 0.7457 | 0.2317 | 0.8601 | 19 |

## DESIGN PRACTICE

In the previous section, the CRITIC–VIKOR method identified creative scheme No. 3 as the optimal scheme. However, a single generated image is insufficient to guide practical manufacturing in furniture enterprises. Therefore, this section further refines the selected scheme through detailed design development and dimensional planning, reconstructing it into comprehensive CAD drawings and a high-precision three-dimensional model suitable for production reference. Rhino 7 was selected as the modeling software due to its well-recognized capability in handling complex and refined surface modeling.

The chair has an overall height of 930 mm, a seat width of 550 mm, and a seat depth of 450 mm. The seat surface is upholstered with beige cotton-linen fabric wrapped around high-resilience foam, which not only retains the skin-friendly and natural texture of cotton-linen materials but also provides good elasticity. The backrest surface is also covered with cotton-linen fabric, while an internal wooden panel provides structural support. The chair legs are slightly splayed outward at an angle of approximately 2°, forming a visually narrower top and wider bottom, which enhances overall visual stability. The main material of the furniture is high-quality brown walnut wood. The exterior surface is finished with a matte varnish and carefully polished, allowing the wood grain texture to appear clear and smooth. In addition, all component edges are rounded rather than sharp, resulting in smoother lines and a more comfortable tactile experience. Overall, the chair exhibits a simple and elegant form. It retains the cultural essence of traditional Chinese furniture while also aligning well with contemporary consumer aesthetics.

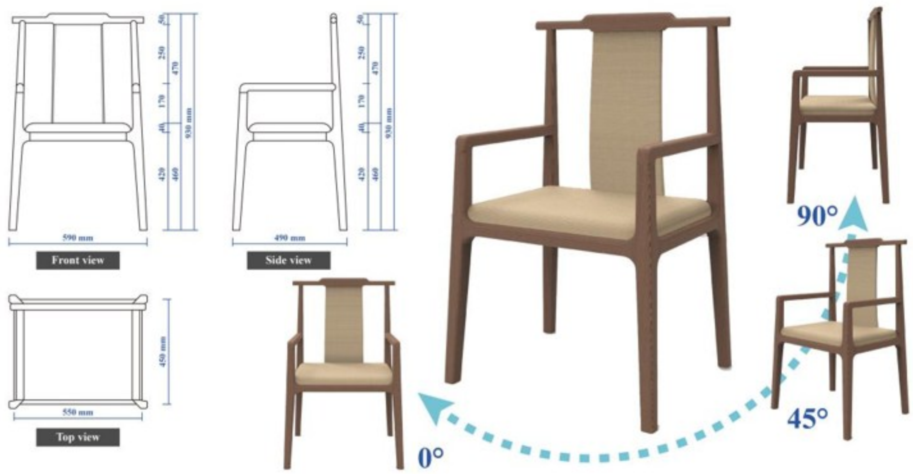


**Fig. 3.** Detailed design of the optimal creative scheme

## DISCUSSION

This study has proposed an integrated creative design and evaluation framework for new Chinese-style furniture that combines stable diffusion with the CRITIC–VIKOR method. As a category of household products that integrates traditional Chinese furniture culture with modern aesthetics and technologies, new Chinese-style furniture has gained widespread popularity among consumers, particularly younger users, and has become one of the most important product types in China's solid wood furniture industry. However, a review of the literature indicated that existing studies primarily have focused on user preference analysis, revealing the perceptual mechanisms underlying contemporary users' evaluations of attractiveness. In contrast, relatively limited research has addressed morphological design innovation, especially studies incorporating advanced AIGC technologies into the creative design process. In practice, product form directly influences users' purchasing decisions and usage experience. Furthermore, industry investigations reveal that many new Chinese-style furniture enterprises continue to adopt traditional design approaches, which rely heavily on the limited experience and expertise of individual designers or design teams. This dependence often results in low R&D efficiency and even creative stagnation. To address these issues, this study integrates the advantages of AIGC technology and multi-criteria decision-making methods to overcome challenges such as design homogeneity and inefficiency inherent in conventional design processes.

On the one hand, in recent years, the use of AIGC and related artificial intelligence algorithms to support design innovation has attracted increasing scholarly attention. By learning from existing datasets, AIGC systems can rapidly generate creative design schemes. Representative generative techniques include GANs, autoregressive generative models, and diffusion models. Compared with traditional GANs and autoregressive models, SD, a diffusion-based model, achieves a favorable balance among stability, diversity, and controllability. It enables high-quality image generation by integrating multimodal inputs, including image data and textual prompts, and can readily produce outputs with resolutions of 512 × 512 pixels or higher. Moreover, earlier generative models typically required training datasets comprising thousands of samples, necessitating substantial time investment in data collection and preprocessing. In contrast, SD supports small-sample training and generation, making it particularly suitable for small and medium-sized enterprises and enhancing the accessibility and practicality of the technology.

On the other hand, although Stable Diffusion shows promising potential in overcoming human creative limitations, it cannot evaluate the quality of generated designs on its own, nor can all generated results be directly accepted without screening. Therefore, manual evaluation and validation of creative solutions are still necessary. Considering the diversity and dynamic nature of real user needs, a multi-criteria comprehensive evaluation can establish a correlation matrix between multiple user requirements and multiple design alternatives, enabling a more holistic assessment of the morphological performance of creative new Chinese-style furniture designs. The CRITIC–VIKOR method can objectively determine the weights of evaluation criteria and provide a comprehensive ranking of design alternatives. Through this quantitative approach, Design No. 3 is identified as the optimal solution with the highest user satisfaction. In terms of the "Minimalist" dimension, the design presents a clean and concise form without redundant components or decorative elements, consisting only of essential load-bearing structures. In the "Comfortable" dimension, both the backrest and seat, which come into direct contact with the human body, adopt upholstered designs that provide a more comfortable sitting experience. In the "Graceful" dimension, the form demonstrates a balanced composition with both square and circular elements integrated harmoniously. In the "Rounded" dimension, all edges and corners are chamfered or rounded, resulting in a softer and safer visual appearance. Although this design does not achieve the highest score in the three individual dimensions of "Minimalist," "Comfortable," and "Rounded," it obtains the highest overall score due to the absence of significant weaknesses. This result indicates that optimizing a single requirement alone does not necessarily lead to better product performance. Designers should focus on improving overall product performance to achieve higher user satisfaction.

It must be acknowledged that this study still has two main limitations that should be addressed in future research. First, although images generated by AIGC provide valuable creative references, the transformation from images into manufacturable engineering drawings and models still largely depends on the time and experience of designers. Future research may explore automation methods for converting images into engineering models to further improve design efficiency and objectivity. Second, this study mainly focuses on form design rather than structural design or ergonomics. Therefore, structural mechanics and comfort performance were not analyzed using finite element analysis (FEA) or ergonomic experiments. Future work may further investigate the integrated optimization of furniture design solutions.

## CONCLUSIONS

1. To overcome the limitations of traditional new Chinese-style furniture form design, which heavily depends on designers' individual experience and available time, this study employed Stable Diffusion (SD) to train and generate a large number of creative images. A high-quality training dataset consisting of 50 images with a resolution of 512 × 512 pixels was constructed for LoRA model training. The SD

model was then utilized to perform rapid image generation, from which 20 representative and high-quality images were selected as creative schemes.

2. To identify the optimal scheme that aligns with contemporary user needs, the CRITIC–VIKOR method was applied to comprehensively evaluate the 20 creative alternatives and assist furniture enterprises in ranking the design options. First, the KJ method was employed to determine four representative user requirements: Minimalist, Dignified, Graceful, and Rounded. Subsequently, the CRITIC method was used to calculate the relative importance (objective weights) of these user needs. Finally, the VIKOR method was applied to compute the comprehensive ranking results, identifying Scheme No. 3 as the optimal solution. Specifically, Scheme No. 3 achieved a group utility value ($S$ values) of 0.2232, an individual regret value ($R$ values) of 0.1174, and a compromise value ($Q$ values) of 0.0000. Based on this outcome, detailed engineering design and modeling were conducted for the optimal scheme.

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