Proceedings of the 4th International Conference on Art, Design and Social Sciences
DOI: 10.54254/2753-7064/2025.27305

A Cultural Symbol–Product Structure Integration Design Method for the AIGC Era

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Abstract. To address the difficulty that generative artificial intelligence (AIGC) faces in deeply and innovatively integrating cultural elements with product carriers in cultural-creative product design, this paper proposes a “demand-modeling — cultural-integration — scheme-generation” design method for cultural-creative products. In the demand-modeling stage, Deepseek-R1 is combined with the Analytic Hierarchy Process (AHP) to precisely identify user needs; in the cultural-integration stage, the concept of Hu moments (invariant moments) and shape grammar are introduced and combined with user requirements to achieve a structured fusion of cultural symbols and product form; in the scheme-generation stage, design proposals are generated using Stable Diffusion (SD) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed to evaluate and select the optimal proposal. A Ming-style hoop-back chair is used as the carrier and Sanxingdui bronze motifs as the cultural elements in a case study. The proposed method is able to achieve deep integration of cultural elements with products while satisfying user needs, effectively bridging the gap between technical rationality and cultural sensibility, and provides new ideas and methods for cultural-creative product design in the artificial intelligence era.

Keywords: Generative artificial intelligence (AIGC); cultural-creative products; Hu moments; Ming-style hoop-back chair; Sanxingdui bronze motifs

1. Introduction

In recent years the cultural-creative industry has developed rapidly and become a new engine of economic growth. As important carriers of cultural transmission and emotional expression, cultural-creative products gain significant added value from the infusion of cultural connotations, which is an important manifestation of their core competitiveness [1]. With the advancement of science and technology, cross-disciplinary innovation has become an inevitable trend in the development of the cultural-creative industry [2]. Introducing AIGC technologies into cultural-creative product design can markedly improve design efficiency and quality and strengthen products’ market competitiveness [3]. In related research, Zhu Kunhao et al. [4] deeply mined typical elements of local culture and, by combining AIGC text-to-image generation, realized local cultural-creative designs that were applied to simple product prototypes, thereby breaking with traditional cultural-creative design forms. However, high-quality renderings cannot be produced from text alone. With the widespread adoption of LoRA and ControlNet, AIGC’s image-generation capability has been greatly enhanced, but Zhou Qiyao et al. [5] pointed out that AIGC merely translates instructions and can easily misinterpret user needs and cultural connotations; moreover, AIGC’s capacity for

DOI: 10.54254/2753-7064/2025.27305

innovation does not entirely surpass traditional creative generation methods, making it necessary to combine AIGC with conventional design approaches. Lu Peng et al. [6] integrated AIGC with AHP and grey relational analysis into the traditional design workflow, while Zhuang Qi et al. [7] optimized the AIGC generation process and proposed a human–machine co-creation design flow: by establishing a material library and increasing human intervention in AIGC's generation process, they successfully applied the Xunpu Zanhuawei IP to the design of cultural-creative footwear, demonstrating that combining human professional knowledge with AIGC merits further in-depth study. Existing studies indicate that although the application of AIGC in cultural-creative product design has attracted wide attention and achieved phased progress, problems persist—such as the dependence of culturally innovative generation on the quality and quantity of training data, severe homogenization of generated content, and the tendency for cultural elements to be mechanically replicated when combined with products, making effective fusion difficult. Therefore, how to realize deep, innovative integration of cultural elements with products while meeting user needs remains a current research hotspot and challenge. To address these issues, this paper proposes a cultural-creative product design method that uses Deepseek-R1 to assist in collecting user requirements and combines this with AHP for demand modeling; introduces the concept of Hu moments and shape grammar to perform cultural integration of cultural symbols with product structures based on user needs; and finally applies TOPSIS to screen SD-generated proposals to complete the innovative design of cultural-creative products.

2. Cultural symbol–product structure integration framework

2.1. Demand modeling

The core functions of DeepSeek-R1 cover natural language processing and real-time online search, enabling efficient information retrieval and processing [8]. In this study, its big-data search capability is used to supplement and comprehensively collect user requirements. Combined with the Analytic Hierarchy Process (AHP), the relative weights of demand indicators are calculated, thereby forming a "comprehensive collection–weight quantification" demand-modeling system. This provides a basis for subsequent product sketch design and for assigning weight values to prompt words in image generation.

2.2. Cultural integration

The concept of Hu moments represents highly condensed image features [9]. By comparing the Hu moments of two images, the similarity of their shapes can be determined. Although widely applied in computer vision, Hu moments have rarely been used in the field of cultural-creative product design. By applying Hu moments, the structural features of cultural elements can be matched with product structures, allowing the selection of cultural element structures that are highly similar to product forms. Shape grammar is then employed to achieve innovative transformations of these cultural element structures. In this way, cultural semantics are preserved while deep innovative integration is realized between cultural elements and product structures, moving from the local level to the overall design. This approach addresses the long-standing challenge of how to achieve profound fusion and innovation between cultural elements and products.

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2.2.1. Scheme generation

Stable Diffusion (SD) is a deep-learning-based generative model with strong capabilities for producing stable and controllable image outputs. It can generate high-quality and diverse images while retaining essential information [10]. In cultural-creative product design, SD effectively preserves cultural characteristics and demonstrates distinct advantages in both the inheritance and innovation of cultural elements [11]. By selecting appropriate models and adjusting parameters, it is possible to generate stylistically consistent images, thus achieving efficient expression of both design sketches and renderings.

Based on the above, a cultural-creative product design model of “demand modeling–cultural integration–scheme generation” is established, as shown in Figure 1.

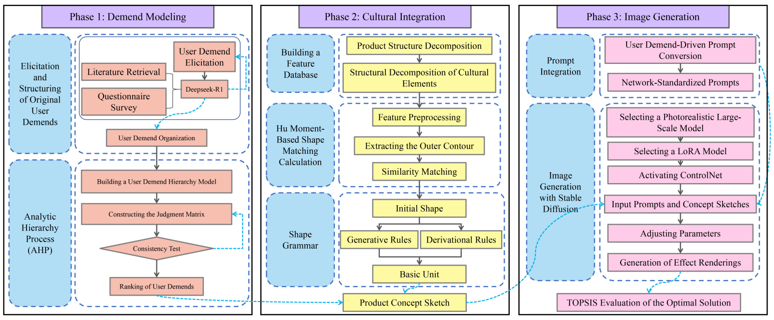

Figure 1. Cultural Symbol–Product Structure Integration Framework

3. Demand model construction

In this study, the Ming-style hoop-back chair is taken as the design carrier, and Sanxingdui bronze motifs are integrated as cultural elements to verify the effectiveness and feasibility of the proposed method.

3.1. Acquisition of user requirements for hoop-back chairs

Requirement information on hoop-back chairs was collected through literature retrieval. Using keywords and derivatives such as “hoop-back chair,” “user requirements,” “user evaluation,” “furniture,” “future,” and “user experience”, searches were conducted in databases such as CNKI and Web of Science, yielding a total of 196 demand terms. With the aid of Deepseek-R1’s online search and data analysis functions, the demand terms were expanded and deduplicated. After integration, 73 user requirements were identified, covering four dimensions: cultural–emotional, appearance design, functional design, and technical craftsmanship.

On this basis, a questionnaire survey was conducted, and 137 valid responses were collected. Deepseek-R1’s data analysis was then applied for further deduplication and refinement, ultimately determining 18 core requirements. A hierarchical model of cultural-creative product design for the hoop-back chair was thus constructed (see Figure 2).

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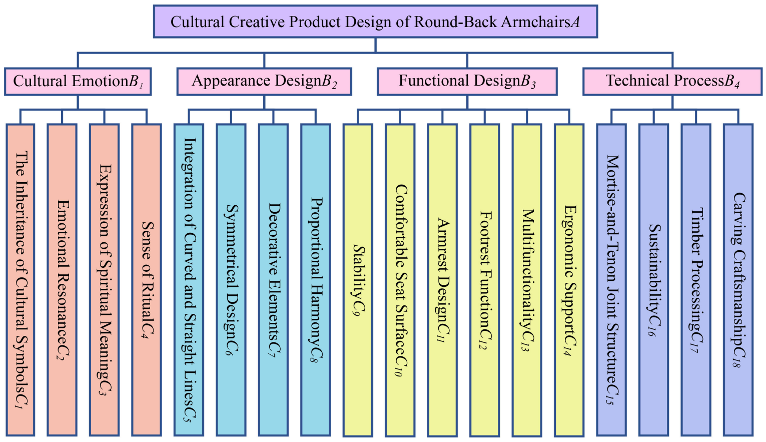

Figure 2. Hierarchical Model of Cultural-Creative Product Design for the Hoop-Back Chair

3.2. Relative weight calculation based on AHP

The Analytic Hierarchy Process (AHP) is a widely used decision analysis method. It decomposes complex decision problems into multiple levels—such as goals, criteria, and alternatives—and employs pairwise comparisons and consistency checks to determine the relative importance of each factor [12]. The steps for analyzing the relative importance of requirements for the Ming-style hoop-back chair are as follows:

First, seventeen participants—including furniture designers, professors of furniture design, and professionals from the furniture industry—were invited to evaluate the requirements for the Ming-style round-back armchair. A pairwise comparison matrix was constructed, and the geometric mean method was applied to aggregate the valid judgment matrices, thereby obtaining the judgment matrix C. Let n denote the number of demand criteria, and let C_{ij} represent the scale value of the importance of criterion C_i relative to criterion C_j. Next, the weight vector W_i of matrix C was calculated as the relative weight value of user requirements.

The consistency index (CI) was used as the consistency verification indicator, and the consistency ratio was calculated as $CR = CI/RI$, where RI was obtained from the reference table.

$$\lambda_{max} = \frac{\sum_{i=1}^{n} C_{ij} \times W_i}{\sum_{i=1}^{n} 4W_i} \tag{1}$$

$$CI = (\lambda_{max} - n)/(n-1) \tag{2}$$

The results showed that all CR values were less than 0.1, indicating that the data are consistent and valid. The relative weights of requirement indicators and their preliminary priority ranking are shown in Table 1.

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Table 1. Results of Relative Weight Analysis of Requirement Indicators

First-level Indicator	Weight	Second-level Indicator	Weight	Relative Weight	Rank	Second-level Indicator	Weight	Relative Weight	Rank
B_1	0.140	C_1	0.471 7	0.066 0	6	C_3	0.164 4	0.023 0	17
		C_2	0.256 1	0.035 9	13	C_4	0.107 8	0.015 1	18
B_2	0.278	C_5	0.390 5	0.108 6	2	C_7	0.195 3	0.054 3	9
		C_6	0.276 1	0.076 8	4	C_8	0.138 1	0.038 4	10
B_3	0.361	C_9	0.088 8	0.032 1	15	C_{12}	0.105 8	0.057 0	12
		C_{10}	0.377 1	0.136 1	1	C_{13}	0.071 8	0.025 9	16
		C_{11}	0.189 4	0.068 4	5	C_{14}	0.167 2	0.060 4	8
B_4	0.220	C_{15}	0.389 1	0.085 6	3	C_{17}	0.157 1	0.034 6	14
		C_{16}	0.174 0	0.003 8	11	C_{18}	0.279 8	0.061 6	7

4. Cultural integration of sanxingdui motifs into the hoop-back chair

4.1. Establishing the feature library

4.1.1. Hoop-back chair feature library

The Ming-style hoop-back chair is one of the most representative seating forms in Ming dynasty furniture. Based on the philosophy of “the round heaven and square earth”, its curved hoop and “S”-shaped backrest are ergonomically designed. Constructed with traditional mortise-and-tenon joints, it embodies both minimalist aesthetics and traditional wisdom. With its concise lines, high-quality hardwood, and interplay of solid and void decorations, it reflects literati aesthetics and ritual culture, making it a classic example of traditional Chinese furniture design [13].

Through literature review and field research in online and offline furniture markets, the main structural components of the hoop-back chair were identified as: hoop rail, armrest, backrest panel, seat surface, apron, legs, footrest stretcher, and struts, as shown in Figure 3. To systematically deconstruct its structural features, a multi-view analysis method was adopted. The chair was decomposed into planar structural diagrams and encoded from A01 to A08 for archival purposes (see Figure 4).

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Figure 3. Structure of the Hoop-Back Chair

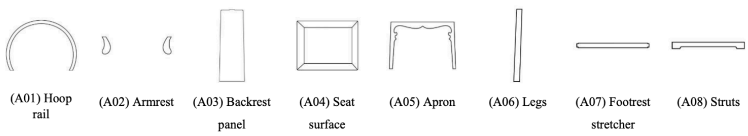

Figure 4. Decomposition of Hoop-Back Chair Structural Features

4.1.2. Sanxingdui motif feature library

The bronze motifs of Sanxingdui are the core visual symbols of Sanxingdui culture. They primarily appear on the surfaces of bronze artifacts and are characterized by abstract patterns and symbolic imagery, including human faces, sacred trees, birds, and animals, all of which embody profound religious and mythological connotations [14]. These motifs usually manifest in composite patterns, consisting of multiple independent elements combined. In product design, directly applying composite motifs often leads to visual information overload, due to their structural complexity, which negatively impacts the overall coordination and functional adaptability of the design. Therefore, decomposing composite motifs into independent patterns not only enhances the applicability of cultural elements but also provides a foundation for subsequent shape matching.

Through on-site research at the Sanxingdui Museum, 34 bronze artifact images were collected via photography. After classification and processing, the motifs were decomposed into independent elements, yielding 81 individual motifs, which were coded as B01–B81. Partial samples are shown in Figure 5.

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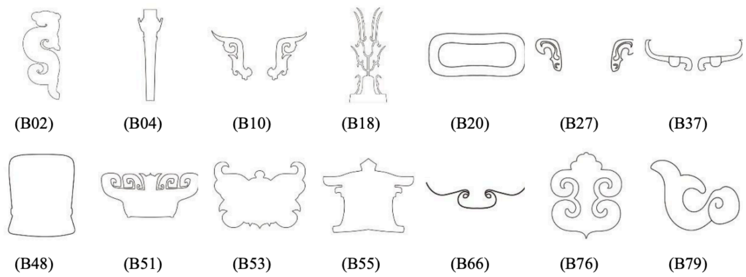

Figure 5. Decomposition of Sanxingdui Bronze Motif Structural Features (Partial Display)

4.2. Similar feature matching based on hu moments

Hu moments, proposed by Hu in 1962 [15], are a method for describing image shape features. They are widely applied in the field of computer vision, such as in pattern recognition, object classification, image coding, and reconstruction [16]. However, research in the field of product design remains relatively underexplored. The major advantage of Hu moments lies in their ability to describe object shapes with translation, grayscale, scale, and rotation invariance [17]. For an image, the Hu moments are defined as follows:

For a discrete digital image $f(x, y)$, where M and N denote the height and width of the image, the $p+q$ -order invariant moment m_{pq} is defined as

$$m_{pq} = \sum_{y=1}^{N} \sum_{x=1}^{M} x^p y^q f\left(x, y\right) \; p, q = 0{,}1{,}2\ldots \tag{3}$$

The $p+q$ -order central moment μ_{pq} is defined as

$$\mu_{pq} = \sum_{y=1}^{N} \sum_{x=1}^{M} (x-\overline{x})^p \left(y-\overline{y}\right)^q f\left(x, y\right) \; p, q = 0{,}1{,}2\ldots \tag{4}$$

The normalized central moment η_{pq} is defined as

$$\eta_{pq} = \mu_{pq} / \mu_{00}^{(1+(p+q)/2)} \tag{5}$$

The Hu moments consist of seven invariant moments, $M1$~$M7$, which are constructed from the second- and third-order normalized central moments. These invariant moments serve as highly condensed image features that mathematically capture the essential properties of an image’s shape. Based on this, the similarity between two images can be distinguished by quantifying the relationship of their invariant moments.

Based on the constructed feature library, the Hu moment algorithm was employed for similarity matching. The Ming-style round-back chair (Ming shi quan yi) embodies the cultural connotation of “round heaven and square earth.” In the feature library, the chair hoop (A01), legs (A06), and footrest stretcher (A07) are retained as the core features reflecting this cultural symbolism. Five structural components—armrest (A02), backrest panel (A03), seat (A04), apron (A05), and stretcher (A08)—were selected for shape matching with 81 independent pattern units (B01–B81) from the bronze pattern library.

Prior to calculation, the original images of A02, A03, A04, A05, A08 and B01–B81 were preprocessed. First, they were converted to grayscale images to reduce dimensionality and

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computational load. Next, binarization was performed, setting background pixels to 0 and target feature pixels to 255 to highlight the primary contour. Finally, Hu moments were used for shape similarity measurement. The top three similarity results are shown in Table 2.

Table 2. Top three similarity matches between patterns and product features

No.	A02	A03	A04	A05	A08
1	B27 (0.172 1)	B20 (0.201 3)	B48 (0.004 3)	B53 (0.827 4)	B61 (0.839 4)
2	B79 (0.227 5)	B55 (0.431 9)	B49 (0.040 3)	B81 (1.960 8)	B68 (1.506 7)
3	B78 (0.275 4)	B51 (0.626 7)	B22 (0.079 5)	B37 (3.118 1)	B58 (1.964 8)

4.3. Shape transformation based on shape grammar

Based on the Hu moment similarity matching results, shape grammar was employed to establish corresponding transformation rules for each similar pattern, enabling systematic design variation. Shape grammar, as a computer-aided design method, generates design elements through formalized rules [18]. Typically, it is defined as a four-tuple: Shape Grammar=(S,L,R,I), where S is a finite set of shapes, L is a finite set of symbols, R is a set of rules (each expressed as a production α→β), and I is the initial shape.

During the evolution process, generative rules (R1: addition, R2: subtraction) and derivative rules (R3: scaling, R4: stretching, R5: mirroring, R6: duplication, R7: rotation, R8: fine adjustment) were applied to ensure that the transformed patterns retained Sanxingdui cultural characteristics while integrating seamlessly with the structural features of the round-back chair. For example, the initial shape B20 evolved into innovative basic unit 01 through the sequence: R7 (rotate 90°) + R2 (subtract) → R8 (fine adjustment) + R1 (add). Other pattern transformations are shown in Figure 6.

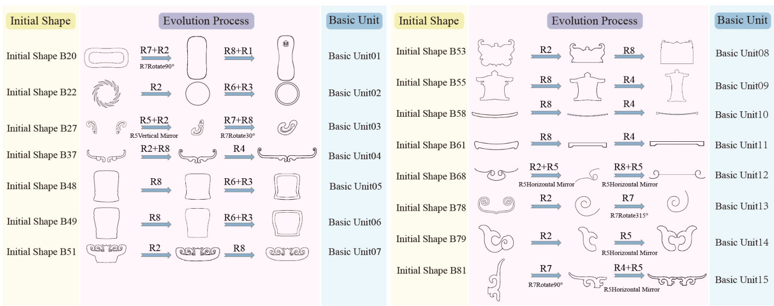

Figure 6. Shape grammar transformation results

4.4. Design concept sketches

Based on the shape transformation results and the relative weighting of user needs, the round-back chair design was developed to address progressive demands, ranging from comfort and practicality to cultural and emotional expression. By integrating traditional craftsmanship with functional requirements, three design sketch proposals were created. For example, in Scheme 1, unit 14 was used for the armrest, unit 01 for the backrest panel, unit 05 for the seat, unit 04 for the apron, and unit 10 for the stretcher, which were combined with the original chair structure to form an innovative design expression. All three design schemes are illustrated in Figure 7.

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(a) Scheme 1 (b) Scheme 2 (c) Scheme 3

Figure 7. Product design concept sketches

5. Sd-based image generation

5.1. Prompt conversion for image generation

To ensure that the prompts are clear and easily interpretable by SD (Stable Diffusion), the user requirements identified above were converted into concrete design elements and expressed in English according to their weight ranking, as shown in Table 3.

Table 3. Prompt conversion results

User-defined Word	Conversion Cues	User-defined Word	Conversion Cues
舒适座面C_{10}	Soft seat cushion	简约C_8	Minimalist
曲线与直线结合C_5	Combination of curve sand straightlines	可持续性C_{16}	Sustainable material sand crafts manship
榫卯结构C_{15}	mortise-and-tenon joint design	脚踏功能C_{12}	Slightly downward curved footrest
对称性设计C_6	Symmetrical over all structure	稳定性C_9	Excellent structural stability
扶手设计C_{11}	Chair with armrest ends gently curve dupward	多功能性C_{13}	Chairs have multiple functions
文化符号传承C_1	Sanxingdui bronze motifs integrated into structure	情感共鸣C_2	Emotional resonance,soulful and meaningful design
雕刻工艺C_{18}	Intricate carved decorations,high-quality texture	木材处理C_{17}	Natural wood finish,smooth wood texture
人体工程学支撑C_{14}	S-shaped curve ature backrest	精神寓意表达C_3	Emphasizing spiritual symbolism
装饰元素C_7	Delicate decorative elements	礼仪感C_4	Artistic and culturally rich

To ensure consistency and high quality in SD-generated images, standardized positive prompt terms such as “white background” and “3D rendering” were added. Negative prompts were collected from professional design websites and industry forums to filter out undesired generation features, thereby forming a complete prompt system. In the design of prompt weights, the comprehensive weight ranking of user requirements was considered: higher-ranked prompts were assigned greater weights within safe limits, lower-ranked prompts were down-weighted, and medium-ranked prompts were not weighted. The resulting positive and negative prompt system is illustrated in Figure 8.

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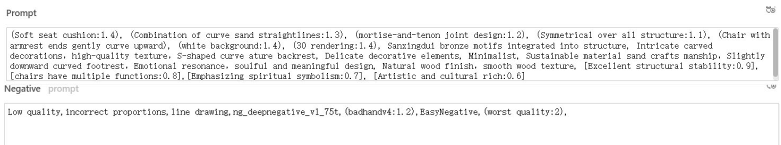

Figure 8. Positive and negative prompt contents

5.2. Product design scheme generation

Using the SD model graphical user interface, the "realisticVision V6.0 B1_V6.0 B1.safetensors" photorealistic model was selected, along with the pre-trained LoRA model "红木圈椅_v2.1:1" from the model library. The ControlNet v1.1.455 module was activated to input the conceptual sketches, allowing local structural constraints to be imposed and preventing structural distortions in the generated images. The specific inputs and parameter settings are shown in Figure 9.

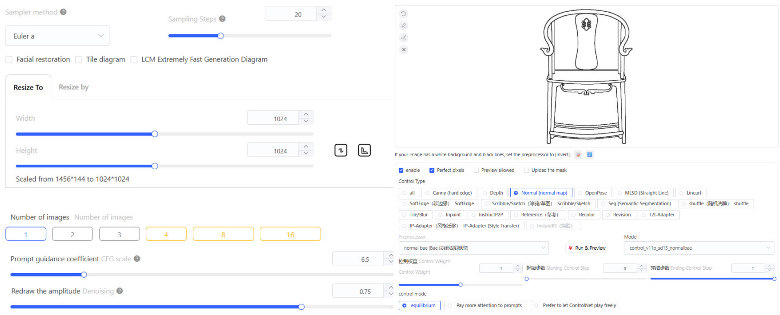

Figure 9. Parameter settings for product design generation

Multiple generation iterations were performed for the three conceptual design sketches, with parameters optimized during the process. Low-quality, overly distorted, and otherwise unsuitable outputs were eliminated. Ultimately, four qualified product design solutions were selected for each of the three sketches, resulting in a total of twelve schemes labeled P1–P12 (Figure 10).

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Figure 10. Generated product design schemes

5.3. Evaluation of design schemes based on TOPSIS

A total of 20 evaluators—including target users, furniture designers, and industry experts—were invited to assess the 12 design schemes. Using the 18 user requirement indicators as evaluation dimensions, the evaluators scored each scheme on a 1–10 scale. Based on the scoring data, a decision matrix was constructed, and the TOPSIS method was applied to calculate the relative closeness of each scheme. The results are presented in Table 4.

Table 4. Evaluation results of generated design schemes

Scheme	Relative Closeness	Ranking	Scheme	Relative Closeness	Ranking	Scheme	Relative Closeness	Ranking
P1	0.980 6	5	P5	0.977 4	8	P9	0.976 1	9
P2	0.980 8	4	P6	0.978 7	6	P10	0.982 1	3
P3	0.978 1	7	P7	0.983 4	2	P11	0.975 4	10
P4	0.987 1	1	P8	0.974 9	12	P12	0.975 3	11

According to the TOPSIS ranking, design scheme P4 was identified as the optimal solution. Structurally, this scheme incorporates a cushioned seat and backrest, a symmetrical overall structure, a downward-curved footrest, and armrest ends gently curved upward. In the comprehensive evaluation across 18 user requirement indicators, P4 demonstrated the best performance, effectively balancing functional needs with ergonomic considerations.

6. Conclusion

This study takes the Ming-style round-backed armchair as the design carrier, integrating Sanxingdui bronze motifs as cultural elements. By employing Deepseek-R1 and the Analytic Hierarchy Process (AHP), user needs for the chair were comprehensively collected and systematically analyzed, yielding precise demand data. Hu moments and shape grammar were then introduced to create

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conceptual design sketches, thereby constructing a pathway for deep integration of cultural elements and product design while effectively avoiding the mechanical replication of cultural symbols. Furthermore, by adopting a human–AI collaborative approach—inputting both user demand keywords and conceptual sketches into the Stable Diffusion (SD) model—the study improved the accuracy of AIGC-generated cultural product designs and ensured the faithful transmission of core cultural semantics. It should be noted, however, that this research focuses solely on the Ming-style round-backed armchair as a single design carrier. The applicability of the proposed method to different cultural carriers and product categories has not yet been tested, and its generalizability remains to be further verified. Future research will extend the approach to design practices across multiple cultural contexts and diverse product categories, thereby conducting multidimensional validation, refining the framework for cultural and creative product design, and enhancing its universality and inclusiveness.

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