Experimental Study on Restoration and Color-Material-Finish Semantic Redesign of Ming-style Yazi Wooden Components Empowered by Generative AI

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This study focuses on the wooden spandrel components of Ming-style furniture to explore the application potential of generative artificial intelligence in the digital preservation and redesign of traditional woodworking cultural heritage. Based on the Dreamina AI platform, a multidimensional Prompt model integrating furniture category, form-feature, and CMF (Colour-Material-Finish) semantics was constructed. From the perspectives of material cognition and ecological reuse, a three-stage experimental path was designed: "Traditional wooden component restoration experiment—Trend CMF semantic experiment—Innovative CMF integrated redesign." The CMF semantic experiment showed that different material and process semantic combinations had a significant impact on aesthetic and innovative perception ($p<0.01$), with the combination of "bamboo + green silk + phoenix embroidery" showing the best performance in terms of ecological aesthetics and cultural expression. The study concluded that generative AI under semantic control can achieve scientific and high-fidelity restoration of traditional components and extend innovative redesign through CMF semantic cultural extension. The openness and semantic construction capabilities of general generative artificial intelligence have introduced new digital expression methods to cultural heritage items made of natural materials, such as bamboo and wood. These methods are forming an interdisciplinary research paradigm that combines sustainable material restoration, cultural semantic control, and AI-driven design.

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INTRODUCTION

Traditional furniture is an important part of China's material cultural heritage. Its form, structure and decoration reflect the aesthetic philosophy and craftsmanship of the East. Ming-style furniture is simple in shape, rigorous in structure and elegant in proportion, representing the pinnacle of Chinese furniture art. Among the components of Ming-style furniture, the apron is a key component that closely combines structure and decorative function. It is located at the lower edge of tables, chairs, stools, *etc.* It serves as a stable supporting surface. Its scroll pattern, pot door, and other shapes carry rich connotations. The apron has a variety of shapes and high precision in detail. It is a representative component that reflects structural logic and aesthetic spirit. However, due to time, material, and preservation conditions, a large number of furniture objects are missing or lost. Existing research primarily relies on literature, catalogues, and line drawings, resulting in the loss of visual, craft, and colour information. Such losses have become a bottleneck for the digital restoration and cultural reproduction of traditional furniture. In recent years, the development of generative artificial intelligence has provided a new technical opportunity for the digital protection and redesign of cultural heritage. AI image generation technology based on a diffusion model can achieve structural restoration, style transfer, and semantic reconstruction under dual constraints of a semantic prompt and a reference image (Liang *et al.* 2024). The use of generative AI facilitates controllable and creative digital restoration of traditional furniture, outperforming conventional modeling in visual and semantic dimensions (Liu *et al.* 2025). Therefore, exploring the application mechanism of AI in the restoration of traditional furniture images and design innovation has become an important research direction for the digital transformation of cultural heritage.

Application of AI in Cultural Relics Restoration and Image

In recent years, AI technology has been increasingly used to protect cultural heritage, especially in image restoration, relic reconstruction, and style transfer. Internationally, scholars such as Guan *et al.* (2025) have used deep generative networks to realize the automatic restoration and style preservation of murals and ancient art images. Wenjun *et al.* (2023) proposed the Stable Diffusion model, which has shown strong semantic understanding and generative control capabilities in text-to-image generation, providing a feasible path for the semantic-driven restoration of cultural images. Related studies in Europe and Japan are also trying to apply diffusion models to the restoration of cultural relic patterns, the piecing together of pottery fragments, and the style redrawing of historical images, to achieve a cross-disciplinary breakthrough from “image completion” to “visual rebirth” (Mendonça *et al.* 2023; Merizzi *et al.* 2024). In China, AI-driven cultural heritage research started late but developed rapidly. Some scholars have used deep learning algorithms to conduct experiments on the restoration of missing areas of murals (Han *et al.* 2025), the reconstruction of ancient book characters (Zheng *et al.* 2022), and the three-dimensional reconstruction of cultural relics (Wang, J. *et al.* 2022). However, most research has focused on restoration at the two-dimensional image level or on digital modelling of the entire object, with less attention paid to the restoration of cultural elements at the component level. AI research on structural crafts, such as furniture, mainly focuses on recognition, classification, and 3D modelling. At the same time, discussions on semantically controllable generation, aesthetic consistency, and cultural continuity of generative AI remain insufficient.

Overall, existing research has three gaps: (1) a lack of research on AI semantic restoration at the component level for traditional furniture; (2) the absence of a scientific verification mechanism between prompt semantic control and image generation effects; and (3) a lack of an AI restoration experimental framework that integrates perceptual evaluation and quantitative indicators. These shortcomings offer this research an opportunity to explore and innovate.

Research Questions

This study focused on the core issue of ‘the controllability and scientific validity of generative artificial intelligence in the restoration and redesign of traditional furniture components’, to answer the following three key questions:

Q1: Can generative artificial intelligence achieve high-fidelity restoration of Ming-style furniture component images under the control of semantic cues and reference images? (Feasibility of AI restoration).

Q2: How will different CMF semantic cues (colour, material and craftsmanship) influence the visual fidelity and aesthetic expression of the generated results? (Mechanism of influence of semantic variables).

Q3: How can a reproducible experimental system and quantitative evaluation indicators be constructed to ensure the reliability and cultural consistency of AI-generated results? (Scientific verification and methodological issues)

These questions focus on how to transform the cultural semantics of traditional furniture into quantifiable, AI-generated variables and on verifying the AI model's performance in the dual tasks of 'restoration-redesign' through systematic experiments. This provides methodological support for the scientific application of generative artificial intelligence in cultural heritage protection.

Objectives and Importance of Research

This study is based on images of furniture components (specifically, the apron-shaped brackets) collected in A Study of Ming Furniture. The use of the Dreamina AI platform enables the construction of a semantically driven image-generation experiment to verify the feasibility and efficacy of generative AI in the restoration and redesign of traditional furniture components. Dreamina AI is used here as a commercial, pre-trained text-/image-conditioned generative platform and is evaluated as a black-box system under controlled prompts (and reference images when applicable), which motivated its selection for the semantic-control experiments. The following research objectives have been identified: Firstly, a multi-dimensional prompt semantic model was constructed, encompassing furniture categories, stylistic features and CMF (Content, Material, Finish) semantic elements, to achieve controllable semantic combination input. Secondly, a reference-image-scale experiment was designed to assess the influence of reference images on restoration quality and stylistic consistency during AI generation. Thirdly, CMF redesign experiments were conducted to compare perceived differences in aesthetic expression and innovation among traditional, trend-setting, and creative CMF semantic combinations. Fourthly, an expert evaluation system was established (to restore accuracy, aesthetics, functionality and innovation) and statistical analysis was conducted. To validate the generated results, this study further introduced a human expert panel to evaluate the outputs from the perspectives of fidelity, aesthetics, functionality, and CMF innovation. Finally, a generative AI paradigm for the restoration and redesign of cultural heritage images was proposed, providing a reproducible technical path and methodological framework for subsequent research. The significance of this study is mainly reflected in three aspects:

Scientific level: Verifying the controllability and stability of generative AI in the restoration of micro-cultural heritage, and revealing the key role of semantic control mechanisms in the quality and style consistency of image generation;

Design level: Exploring the potential of AI in cultural redesign and aesthetic innovation, and providing an operable experimental path for the digital transformation and contemporary redesign of traditional crafts;

Cultural dissemination level: Emphasising the potential of general AI technology in lowering the threshold of cultural heritage research, promoting public participation and knowledge sharing, and proposing new ideas for realising the open, visual and living inheritance of cultural heritage through AI.

Advances in Cultural Heritage Digitisation and Restoration Research

With the rise of digital humanities and cultural computing, cultural heritage preservation has gradually shifted from a traditional model centred on physical restoration to a systematic approach focused on digitisation, intelligence, and visualisation. Scholars generally believe that digital technology can play a crucial role in non-destructive restoration, multimodal recording, and cultural semantic reconstruction (Jin and Liu 2022; Breathnach and Margaria 2023; Zhang *et al.* 2025).

Internationally, research on cultural heritage digitisation has undergone a multi-stage evolution from static recording (2D scanning, photogrammetry) to dynamic reconstruction (3D modelling, texture mapping), and then to AI-assisted restoration. Recently, the application of artificial intelligence and computer vision methods to the automatic stitching and digital restoration of fragmented cultural relics has gained significant traction. For example, Münster *et al.* (2024) pointed out that, with the help of deep learning and computer vision technology, damaged murals or pottery fragments can be automatically spliced, color regenerated and structurally reconstructed; Marconi *et al.* (2023) proposed an AI-assisted digital reconstruction method for archaeological pottery, which can effectively improve the accuracy of automated restoration of damaged objects. These studies show that AI technology is driving the digital protection of cultural heritage — from "recording" to "cognitive reconstruction" — providing a new path for the intelligent restoration of complex cultural relics. In China, the digitalisation of cultural heritage has become one of the key national scientific research directions. In the collaborative project between Peking University, the Academy of Arts & Design of Tsinghua University and the Dunhuang Academy, AI-assisted "mural damage repair" has been able to achieve regional image completion based on style transfer algorithm (Li *et al.* 2022); Zhejiang University, the Central Academy of Fine Arts and other institutions are also exploring the reconstruction of ancient book characters and pattern generation based on GAN and diffusion model (Zhang *et al.* 2023). These achievements signify that AI technology has gradually expanded from the restoration of artistic images to the deep reconstruction of cultural visual semantics.

Existing research primarily focuses on two-dimensional or complete objects, such as murals, paintings, calligraphy, and artefacts, with insufficient attention to component-level cultural heritage restoration. Especially in furniture-related heritage, components convey formal information and exhibit structural and mechanical logic; the scientific validity and interpretability of AI restoration warrant further in-depth exploration.

Evolution of Generative Artificial Intelligence in Image Restoration and Reconstruction

Generative artificial intelligence has completely reshaped the technological landscape of image restoration and design innovation. Early research mainly focused on convolutional autoencoders (autoencoders) for local encoding and decoding restoration of damaged or missing image regions. The introduction of generative adversarial networks (GANs) enabled models to achieve stronger semantic understanding—the discriminator not only evaluates the "realism" of the generated results but also prompts the generator to reconstruct missing regions based on image context and semantic information. According to the latest review, this evolutionary path is clearly visible (Xu *et al.* 2023). GAN-based methods have improved the realism and consistency of results, but significant problems remain. The content is often unstable and changes significantly in style (*e.g.*, the style or colours differ from the original image) (Weng *et al.* 2022).

The diffusion model is a significant step forward in how we think about generative tasks. The "High-Resolution Image Synthesis with Latent Diffusion Models" paper by Rombach and others (2022) proposes a way to control what the model sees while preserving its structure. It is done using a "noise-anti-noise" process that is repeated multiple times. In practice, this process can be combined with text instructions, reference images, and control modules (such as ControlNet) to achieve "conditional generation". When it comes to cultural heritage, the use of generative AI has moved beyond simply restoring images to creating new ones with the same meaning and style. Researchers think that "Prompt Engineering" is a key way to making images with generative AI. Users can control the words and images in a specific style or cultural context by adjusting the lexical structure, semantic level, and parameters of the prompt words. Recent research goals include making prompts more effective for style control (Oppenlaender *et al.* 2025) and improving the model's ability to match different cultural nouns (Ventura *et al.* 2025). This technical approach creates a "semantic bridge" for the digital reproduction of traditional visual culture, enabling AI to shift from being a "redrawing tool" to being a "cultural semantic regeneration medium." However, there are still three challenges that current AI technology has to overcome: (1) The way that the meaning of the results changes; (2) the lack of a system for evaluating image restoration that is the same for everyone; and (3) the differences between how people and computers understand words. To make generative AI easier to understand in the study of cultural heritage, there is a need to develop a research framework that incorporates semantic controllability, statistical verification, and cultural matching.

Current Status of Digital Research on Furniture Components and Traditional Craftsmanship

Digital furniture analysis requires an understanding of structural systems, materials, and fabrication principles. Current research follows three main paths. The first centres on structural digitisation—parametric modelling of mortise-and-tenon joints and Yazi components, extending Wang Shixiang's foundational work using tools such as Revit and Rhino-Grasshopper for 3D visualisation and performance simulation (Xu *et al.* 2023; Chen *et al.* 2024; Wang *et al.* 2024). Symbolic interpretation in design and art history examines motifs including scrolls, clouds, and phoenixes across cultures, tracing their semantic evolution. Such studies remain descriptive and seldom apply AI-based semantic annotation methods (Xue *et al.* 2024). AI-driven design has been introduced to traditional crafts using generative models to create patterns and parameterized forms. Most of these efforts remain just ideas, with little real-world evidence to support them or a precise research method (Lai *et al.* 2024). Researchers have studied this topic before, but there are still problems. There is not much information available, models cannot generate new information, and evaluation systems are not very good. Integrating structure, style, and cultural meanings into AI-driven creation, especially in details, remains a significant research problem.

The Generation of Content Based on Semantics, along with the Redesign of Cultural Heritage

Semantic-controlled generation is a very advanced area of research in generative AI. The main idea is to create a prompt structure that is understandable and can be used to control the results. This is done by using clear semantic variables (for example, material, colour, and process). It is noted that the design of the prompt structure determines the semantic accuracy and cultural adaptability of AI-generated images, constituting a "new design language" in the AIGC era (Wang *et al.* 2024). In cultural heritage research, semantic control not only means the form of reproduction, but also involves the preservation of cultural imagery and cognitive symbols. Researchers have proposed the "CMF semantic encoding" (Colour – Material – Finishing Encoding) to parameterise materials, colours, and processes, thereby establishing a cultural semantic space that AI can understand (Valan and Paglierani 2024).

However, there is currently a lack of research on prompt structures based on cultural semantic systems. Most AI generation is still at the stage of empirical prompts, making it difficult to guarantee the reproducibility and quantitative comparability of the results. Furthermore, the redesign of cultural heritage requires not only the "innovation" of the generative model, but also a balance between "cultural acceptability" and "traditional continuity." This demands that AI systems understand the deep semantics of cultural images, rather than merely replicating their visual forms.

Based on this, this paper constructs a multidimensional semantic variable model. It uses the Prompt engineering method to guide AI in achieving controllable expression of cultural semantics during generation. Statistical experiments are then used to verify the scientific feasibility of generative AI in the restoration and redesign of traditional furniture components.

EXPERIMENTAL

Research Framework and Procedure

This study explored the semantic controllability and expression mechanisms of generative artificial intelligence in the restoration and redesign of traditional furniture components.

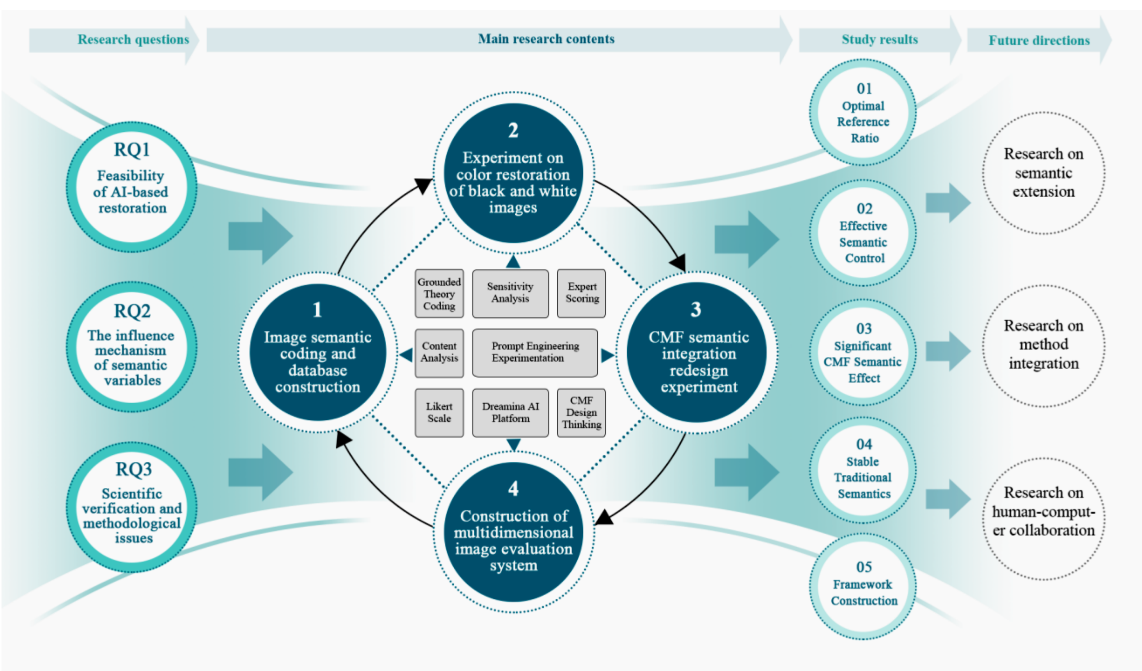

Fig. 1. Overall research framework and experimental flowchart

Centred on the core question—how AI interprets and reconstructs the cultural semantics of Ming-style furniture—a comprehensive technical framework was developed (Fig. 1), featuring component-level semantic control and the Dearmina AI platform as the experimental environment.

The overall research logic follows a three-stage structure: semantic modelling, generative experiments, and evaluation analysis. First, 138 image samples of Yazi components were extracted from Studies on Ming-style Furniture, and they were combined with textual descriptions to build a multi-dimensional semantic dataset covering structure, form, ornamentation, and craftsmanship. Using grounded theory coding (Glaser *et al.* 1968), semantic elements were categorised into three core variable dimensions: F-type (furniture type semantics), S-type (component form semantics), and C-type (CMF: colour, material, and finish semantics), providing systematic support for prompt design in generative AI.

Two main experiments were conducted:

Image Restoration Experiment: Using traditional CMF semantics (C01: huanghuali wood + natural tone + carving) as a baseline, the F and S variables were manipulated to examine how furniture categories and Yazi shapes affect the structural fidelity and stylistic consistency of AI-generated outputs;

CMF Redesign Experiment: With fixed F and S semantics, C-type variables (C02–C06) were replaced to test traditional, trending, and creative CMF combinations, aiming to compare aesthetic performance and innovation potential across different material and craftsmanship semantics.

In the experimental evaluation stage, the expert scoring results were integrated to construct a comprehensive evaluation system covering four dimensions: fidelity, aesthetics, functionality, and innovation. Analysis of variance (ANOVA) and significance testing methods were used to verify the perceptual effect and statistical correlation of semantic control on the generated images. The overall framework used a closed-loop logic from semantic input to generated output, which ensured that the AI generation process could be controlled and understood, and which provided a replicable experimental paradigm for the visual reconstruction of cultural heritage.

Construction of the Semantic Dataset of Ming-style Yazi Components

To conduct image-generation experiments driven by semantic control, this study first constructed a semantic dataset of Ming-style Yazi components, serving as the most fundamental and crucial semantic input throughout the research process. This data set was taken from the text and pictures in Wang Shixiang's important book, "A Study of Ming-style Furniture." It includes 138 examples of furniture from Yazi, accompanied by black-and-white photographs and drawings that illustrate their assembly. The samples include various types of furniture, including chairs, tables, beds, and cabinets. This makes sure that the samples are a good representation of the types of furniture and how they are made.

In the data extraction stage, the study adopted a component-centred analysis strategy, using the Yazi as a semantic anchor. Combining textual descriptions, image features, and furniture type, the Yazi information for each sample was annotated and extracted line by line. After that, Grounded Theory was used as a coding method. This method used open coding and axial coding to systematically combine and summarise the features, formal language, and craft attributes.

After many rounds of manual annotation and expert review, five main semantic dimensions were identified: F01 Furniture Type, which includes tables, chairs, stools, cabinets, *etc.*; S01 Structural Feature, which includes aprons, cloud-patterned aprons, and arched aprons; D01 Decorative Style, which includes cloud patterns, phoenix patterns, lotus patterns, and scrolling grass patterns; P01 Processing Technique, which includes openwork carving, hollowing, mortise and tenon joints, and carving; and M01 Material Attribute,which includes rosewood, sandalwood, bamboo, and acrylic.

Under this semantic structure, a total of 621 original semantic terms were extracted. After multiple rounds of normalization, semantic deduplication, and structural merging, 117 core component-level semantic vocabulary items (Yazi Semantic Vocabulary) were finally formed. This vocabulary is characterized by clear hierarchy, comprehensive semantic coverage, and operable combinations, and can directly support multi-platform Prompt input and semantic-variable control experiments.

The whole dataset was built using a ternary mapping structure of "semantic dimension—component image—keyword." Each word has a specific image and a text that explains it. Together, these words form a table that can be indexed and traced. The research team used Excel and JSON for storing data in a structured way. It used Python to analyze data and create visualizations, including word clouds and networks that show how different ideas are connected (Fig. 2).

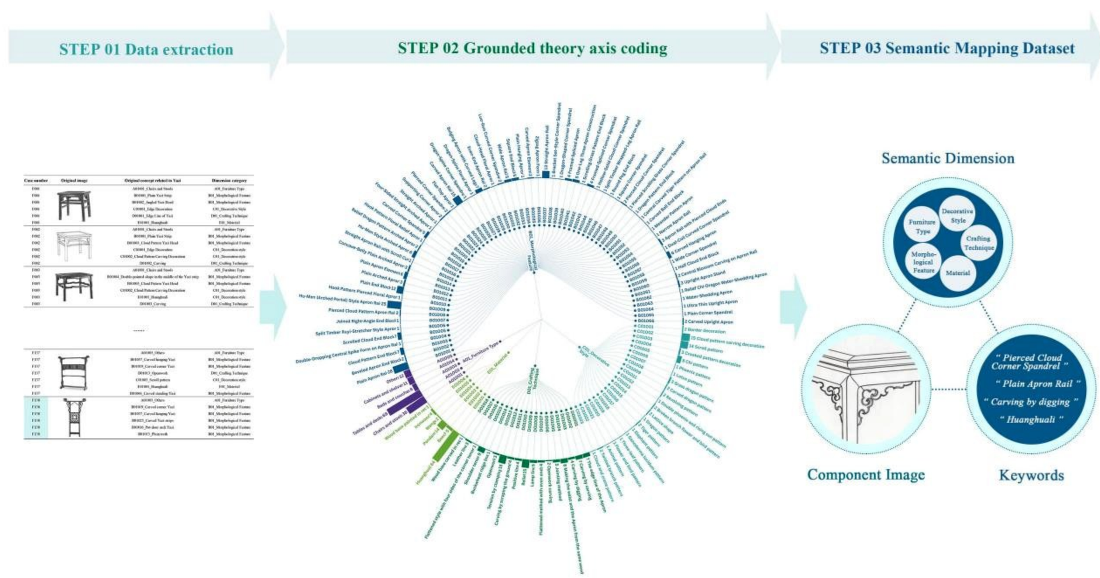

Fig. 2. Flowchart of the construction of the semantic dataset of wooden apron structure of Ming-style furniture

This semantic dataset allows traditional craft images to be converted into computable semantic models, providing a structured input source for Prompt-based semantic modelling. This is different from previous methods that relied solely on visual recognition or text annotation. This study introduced semantic encoding logic and hierarchical modelling methods. These methods enabled the AI generation system to express cultural semantics in a structured way. This creates the foundation for later image restoration and redesign experiments. It also provides a knowledge system and methodological paradigm for digitally reproducing traditional crafts.

Prompt Semantic Modelling and Variable Definition

After constructing the Ming-style Yazi semantic dataset, this study further transformed the semantic information into structured input instructions recognisable by generative AI to achieve semantically controllable image generation. This section aims to elucidate the semantic modelling logic and variable-definition method of the prompt, providing a foundation for subsequent image restoration and redesign experiments.

Prompt structure design principles

Generative AI models (such as Dreamina AI) create images by decoding and visualising the meaning of the text. The way different words and phrases are combined and arranged in the prompt words directly affects the style, structure, and how true to the original meaning the generated text is. Therefore, it is important to create a clear and simple structure for the instructions. This will help to control the meaning when making Ming-style furniture parts.

Based on the multidimensional features extracted from the semantic dataset, this study designed a modular Prompt Structure Model to uniformly control the input semantic dimension and generation logic, as follows,

$$P = [R_w] + [F_{type}] + [S_{form}] + [C_{cmf}] + [A_{aux}] + [B_{bg}] \tag{1}$$

where $[R_w]$ represents the Reference Image Weight, controlling the degree of dependence of the generated image on the original sample, and is a key variable affecting structural fidelity; $[F_{type}]$ represents Furniture Type Semantics, defining the functional attributes and cultural context of the overall object (*e.g.*, "table", "chair", "stool"); $[S_{form}]$ refers to Structural Form Semantics, describing the shape features and decorative structure of the railing(*e.g.*, "curved Yazi rail with cloud motif"); $[C_{cmf}]$ is short for CMF semantic variables. These variables control the semantics of material, colour, and craftsmanship. For example, they can be used to specify a rosewood texture,a carved pattern, or a matte finish. $[A_{aux}]$ represents Auxiliary Description, which is used to refine the rendering appearance, such as "high detail, single component, isolated object"; $[B_{bg}]$ represents the Background setting. (Settings) ensure that the generated results have a visually consistent compositional logic, such as "white background, soft lighting".

This structure connects semantic data to generated statements in a straightforward way, enabling the AI model to understand and reproduce the meaning of traditional components based on instructions organised in a hierarchy. This ensures the results are consistent in meaning and relevant to the culture. This Prompt model can be adjusted to different project goals, such as restoration or redesign, because it is flexible and adaptable. This model can control the generation of multiple levels, with control based on the meaning, or "semantics," of the content.

Semantic variable definition and hierarchical control

To systematically reveal the role of different semantic dimensions in the generative AI image generation process, this study hierarchically defined and encoded the core semantic variables in the Prompt input to ensure the controllability of the experimental process and the comparability of the results. The semantic variable system included three categories: furniture type variables (F category), structural form variables (S category), and CMF semantic variables (C category). Among them, the F category was used to limit the overall category and cultural context of the generated object, mainly covering types such as tables, chairs, and armchairs, which determines the macroscopic proportion and component layout characteristics of the AI-generated image; the S category focuses on the shape characteristics and formal language of the apron components, including semantic units such as cloud-patterned aprons, arched aprons, and openwork cloud-patterned aprons, which are key factors affecting the local structure and morphological recognition of the generated image; the C category, as the core variable of this study, controls the color, material, and craftsmanship characteristics of the generated image, which is directly related to the stylistic consistency and perceptual innovation of the generated result. To make sure that the coverage of different variables is balanced and that the layers of meaning are logical, Category C semantics is divided into three groups. The first group is the traditional CMF combination (C01), represented by "huanghuali wood + natural wood colour + carving technique," which reflects the typical material semantics of Ming-style furniture. The second group is the trend CMF combination (C02–C04), including "recycled wood chips + 3D printing," "ceramic collage + brick red texture," and "recycled plastic + colored shavings remoulding," which reflect the design orientation of contemporary materials and sustainable processes. The third group is the creative CMF combination (C05–C06), such as "bamboo + phoenix pattern embroidery" and "vibrant acrylic + peony openwork carving," which aim to test the limits of generative AI in recreating cultural symbols and integrating their meanings.

New materials: This semantic layering and encoding mechanism allows Prompt to combine and control semantic dimensions at the input stage. This enables generated results to form an analyzable semantic mapping of macrostructure, local shape, and surface craftsmanship. This helps make the experiment more organized and reproducible. It also provides a clear understanding of the data and a theoretical basis for subsequent statistical analysis and evaluation.

Experimental Design for Image Restoration and Redesign

After completing semantic modelling and Prompt structure construction, this study designed two core experiments to verify the feasibility and performance differences of generative AI in the semantic restoration of traditional furniture components and the reconstruction of contemporary designs. The entire experiment was conducted on the Dreamnia AI platform, maintaining consistent model versions and parameters to ensure comparability and statistical reliability of the results.

The Image Restoration Experiment aimed to examine the structural fidelity of generative AI under semantic control. The experiment fixed the CMF semantics to a traditional combination (C01: rosewood + natural wood colour + carving). The experiment then varied the input semantics (F) and component shape semantics (S), testing the impact of different semantic combinations on image restoration accuracy and style consistency while keeping the Prompt structure unchanged. Simultaneously, by adjusting the "reference image parameter ratio" (0.1-1.0), the balance between semantic guidance and image reference in result generation was compared to determine the optimal control range.

The Redesign Experiment focused on the innovative expression and cultural extension of CMF (Content, Material, and Finish) semantic variables. The experiment fixed the furniture type and the semantic meaning of the ridge ornaments, only changing the CMF (Content, Material, and Finish) cue word combinations, including the traditional semantic group (C01), the trend semantic group (C02–C04), and the creative semantic group (C05–C06). By systematically replacing words with different labels, it was possible to explore how material, colour, and craftsmanship affect images in relation to Chinese beauty standards and how they combine traditional and modern design.

All experiments used the same settings for image resolution, number of sampling steps, CFG intensity, *etc*., and a unified prompt template and a fixed set of negative cue words to reduce the effects of factors unrelated to meaning. There were three samples for each word group, and the best images were selected to study later. Information about the experimental outputs was recorded to ensure the research could be repeated and the results checked.

The study used two types of experiments to create a closed-loop verification system. This system focused on semantic control, image generation, and perceptual evaluation. It provided basic data support for the structural fidelity test, expert scoring analysis, and significance statistics in later chapters.

Multi-dimensional Evaluation System

To systematically evaluate the performance of generative artificial intelligence in the image restoration and redesign of Ming-style furniture apron components, this study constructed a multi-dimensional evaluation system based on expert scoring to ensure the scientific rigour of the results analysis and the effectiveness of the cultural interpretation. A human expert panel was employed to quantitatively assess the quality of the AI-generated images. Specifically, an expert panel of eighteen judges independently evaluated the generated results across four dimensions: restoration fidelity, Chinese aesthetic expression, functional and practical expression, and CMF integration innovation. The goal was to reveal the performance patterns of the mechanisms that drive semantic generation in the visual restoration of cultural heritage. The experts were from different fields, including furniture design, traditional crafts, artificial intelligence, and cultural heritage protection. All experts had much experience in academic research or industry practice, which ensured that the evaluation process was interdisciplinary and professional. To make the scoring more consistent and reliable, all experts received the same instructions and training on the features of Ming-style furniture and the scoring dimensions before the formal scoring. This ensured that everyone understood how to evaluate the pieces.

This study used a Likert scale that ranged from 1 (very low) to 5 (very high) to systematically evaluate the generated images across four main categories. The first dimension, “Accurate Reproduction of Ming-Style Furniture,” looks at how well the images match the real thing in terms of shape, size, and how they are decorated. The second part of this study, “Expressiveness of Chinese Aesthetics,” looks at how the cultural style and overall beauty of the generated images match up. The third dimension, “Functionality and Practicality,” focuses on how well the components are designed, how stable they are, and how easy they are to use. The fourth dimension, “Innovative Integration of Materials, Colors, and Craftsmanship,” looks at the creative mix of materials, colors, and craftsmanship meanings in the created images and their cultural impact. After standardising and coding the data, the expert scoring data were put into SPSS software for statistical analysis. To start, math methods were used to calculate the mean, variance, and range of each dimension. We did this to find the overall trend as well as the differences. One-way ANOVA was used to test how important different combinations of variables (including furniture category, styling, and CMF semantics) were in the scores. Finally, Tukey post-hoc comparisons were used to determine the sources of differences and clarify the sensitive variables and influencing patterns of AI generation effects under semantic control.

This evaluation system, centred on subjective aesthetic perception, reflected the experts’ overall trends in perception of the cultural semantic restoration and stylistic expression of AI-generated results, showcasing the recognizability and cultural adaptability of different semantic combinations in design expression. This research differed from traditional methods of evaluating image quality by focusing on ensuring that images matched and reflected the cultures they represent. It also let people interact with how they felt about the images and understood the culture behind them. By establishing a multidimensional evaluation framework grounded in expert perception, the scientific rigour and repeatability of the evaluation results were ensured, providing an operational evaluation model and paradigm for generative AI applications in cultural heritage image restoration and design innovation.

RESULTS AND DISCUSSION

Experiment 1: Reconstruction Experiment of Yazi Structure

To ensure the stability and controllability of the large-scale Ming-style furniture image reconstruction experiment, this study first conducted a small-sample pre-experiment on the key control variable in generative AI image generation—the "Reference Image Weight." The experimental goal was to explore the sensitivity of this parameter to AI image reconstruction performance, thereby determining the optimal parameter setting and providing a technical basis for subsequent batch reconstruction of 138 furniture images.

Pre-experiment on reference image weight

In the pre-experiment stage, four representative sets of Yazi component image samples were randomly selected from "Research on Ming-style Furniture," covering both line drawings and black-and-white photographs. By adjusting the "Reference Image Weight" (*i.e.*, ControlNet weight) in the input Prompt, ten gradients were set sequentially: 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and 100%. While maintaining consistency in other semantic dimensions, a unified Prompt format was adopted:

[*Reference Image Proportion*] + [*Ming-style furniture*] + [*white background*] + [*colour*] + [*material*] + [*craft*]

Group testing was then conducted on the Dreamnia AI platform, and the resulting sample results are shown in Fig. 3.

Fig. 3. Comparison of the generation effect with changes in the proportion of parameters in the outer contour reference image (0.1-1.0)

To improve the objectivity and statistical rigour of the evaluation of the restoration effect, this study used a 5-point Likert scale with anchored descriptions. Three experts specialising in traditional furniture and graphic techniques were invited to conduct blind scoring of the generated results under four reference image weights (0.6, 0.7, 0.8, and 0.9). The dimensions included "overall form consistency," "identifiability of the Yazi components," "style reproduction," "material and colour responsiveness," and "component detail expression." Each expert reviewed four images from the same sample under each weight, scoring them on each of the five dimensions. The median of the experts' responses was taken as the representative value for that weight. As shown in Table 1, the statistical analysis first assessed expert consistency (Kendall's W), then used the Friedman test to compare differences across the four weights within each dimension, and finally employed the Wilcoxon paired test (Holm corrected) for post-hoc comparisons. The results showed that the scores given by experts were mostly the same within a range of 0.6 to 0.9 (Kendall's W≈0.66 to 0.74), but there were also big differences between groups in most dimensions ($p<0.05$). After doing more in-depth comparisons, it was found that a weight of 0.8 was much better than 0.6 across all five dimensions. However, they were not significantly different from 0.7 or 0.9. This suggests that 0.8 strikes a good balance between keeping things the same and allowing freedom. Therefore, in this work the reference graph weight was set to 0.8 as the standard for subsequent large-scale restoration experiments.

Table 1. Impact of Reference Map Weights on Restoration Quality: Median Expert Rating [IQR] (n=3 experts)

Evaluation Dimensions	0.6	0.7	**0.8**	0.9	Kendall's W	Friedman χ^2 (df=3)	p-value	Host-hoc comparison (Holm corrected)
Overall form consistency	3.0 [3.0–3.5]	4.0 [3.5–4.0]	**4.5 [4.0–5.0]**	4.0 [3.5–4.0]	0.74	11.6	0.009**	0.8>0.6*, 0.8>0.7 ns, 0.8>0.9 ns
Identifiability of the Yazi components	3.0 [3.0–3.5]	4.0 [3.5–4.0]	**4.5 [4.0–5.0]**	4.0 [3.5–4.0]	0.71	10.9	0.012*	0.8>0.6*, 0.8>0.7 ns, 0.8>0.9 ns
Style reproduction	3.0 [2.5–3.5]	4.0 [3.5–4.0]	**4.5 [4.0–5.0]**	4.0 [3.5–4.0]	0.69	9.8	0.020*	0.8>0.6*, other ns
Material and colour responsiveness	3.0 [3.0–3.5]	4.0 [3.5–4.0]	**4.5 [4.0–5.0]**	4.0 [3.5–4.0]	0.66	9.2	0.026*	0.8>0.6*, other ns
Component detail expression	3.0 [2.5–3.5]	4.0 [3.5–4.0]	**4.5 [4.0–5.0]**	4.0 [3.5–4.0]	0.73	11.1	0.011*	0.8>0.6*, other ns

Specifically (Fig. 4), when the reference image accounts for too high a proportion, the AI tends to replicate the visual noise and local defects of the original image during generation. For example, at a weight of 90% (0.9) (d09), the apron that should have presented an "embossed" effect was mistranslated as "openwork," resulting in a semantic shift; at a weight of 100% (1.0) (d10), some "rosewood" wood was misidentified by the AI as a highly reflective veneer material, presenting a distorted metallic texture. The image at a weight of 80% (0.8) (d08) performed best in terms of overall structure, pattern layering, and detail clarity. It preserved the structural features of the original image while expanding its semantics at the texture and colour levels.

AI image restoration was found to work best with 80% black-and-white or line-drawing input, balancing fidelity and control while minimising errors. Therefore, this study used 80% as the standard parameter for subsequent Ming-style furniture restoration and redesign experiments to ensure the repeatability, interpretability, and high fidelity of the generation process.

Fig. 4. Comparison of generation details under different parameter percentages (80 to 100%)

Semantic-driven image restoration experiment

After figuring out that 80% was the best image ratio, a big-picture experiment to restore Ming-style furniture apron pieces officially got underway. The test subjects were 138 black-and-white images of furniture (including line drawings and photographs) collected from Wang Shixiang's "Studies on Ming-style Furniture." The images included chairs, stools, tables, beds, and cabinets. All images were put in with an 80% reference image ratio, and all of the questions were built using words from a semantic database.

Semantic keywords were selected from the Yazi Semantic Vocabulary. These included "pot-shaped apron," "dragon-pattern carving," "edge line," "mortise and tenon structure," and "huanghuali wood material." This was done to ensure that the content of the generated task matched the content of the original image.

Fig. 5. Comparisons between restored image and original sample of Ming-style furniture

The generated results are shown in Fig. 5. Compared with the original black-and-white image, the AI-generated image achieves high fidelity in component structure, decorative details, and colour representation. Especially in complex components such as the "pot-shaped apron" and "openwork apron," the model can accurately respond to the shape and craftsmanship information involved in the prompts. This demonstrates that the semantically driven Prompt structure has significant semantic control over image restoration.

Component-level reconstruction and local extraction

To further focus on the hierarchical structural features of apron components, this study adopted a "holistic generation—local extraction" approach. That is, using the entire piece of furniture as the generation object, semantic cues were used to focus on the apron region. After generation, the apron parts were manually extracted from the complete furniture image, forming a component-level reconstruction image set.

In the batch reconstruction of 138 images, the research team categorised and numbered 66 types of apron components, summarised using grounded theory (Fig. 6), ultimately constructing a "Ming-style Apron Component Image Reconstruction Comparison Atlas" that demonstrated the multidimensional correspondence between AI-generated and original samples (Fig. 7). This atlas not only provided a quantitative basis for subsequent structural similarity and perceptual evaluation but also provided intuitive visual evidence for the scientific verification of generative AI in the reconstruction of cultural heritage components.

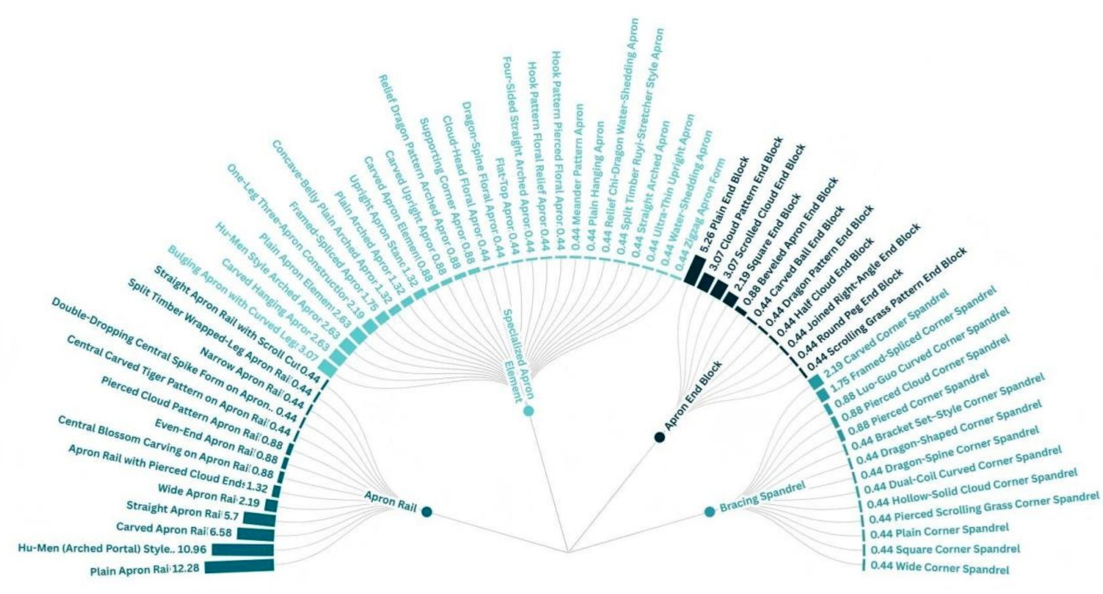

Fig. 6. Statistical chart of 66 types of Yazi components

The Dreamina AI tool was tested by comparing image ratios and restoring images at scale. This confirmed that the Dreamina AI tool can be used reliably to restore images. This evaluation is achieved through the implementation of reference-image parameter ratios and large-scale, semantically driven restoration experiments. The results show that an 80% reference image ratio achieved the optimal balance between structural fidelity, semantic response, and visual performance; the semantic cue word structure played a significant role in controlling the generation direction and style consistency. The results of this experimental phase provided a solid technical and data foundation for subsequent redesign experiments and expert perception evaluation.

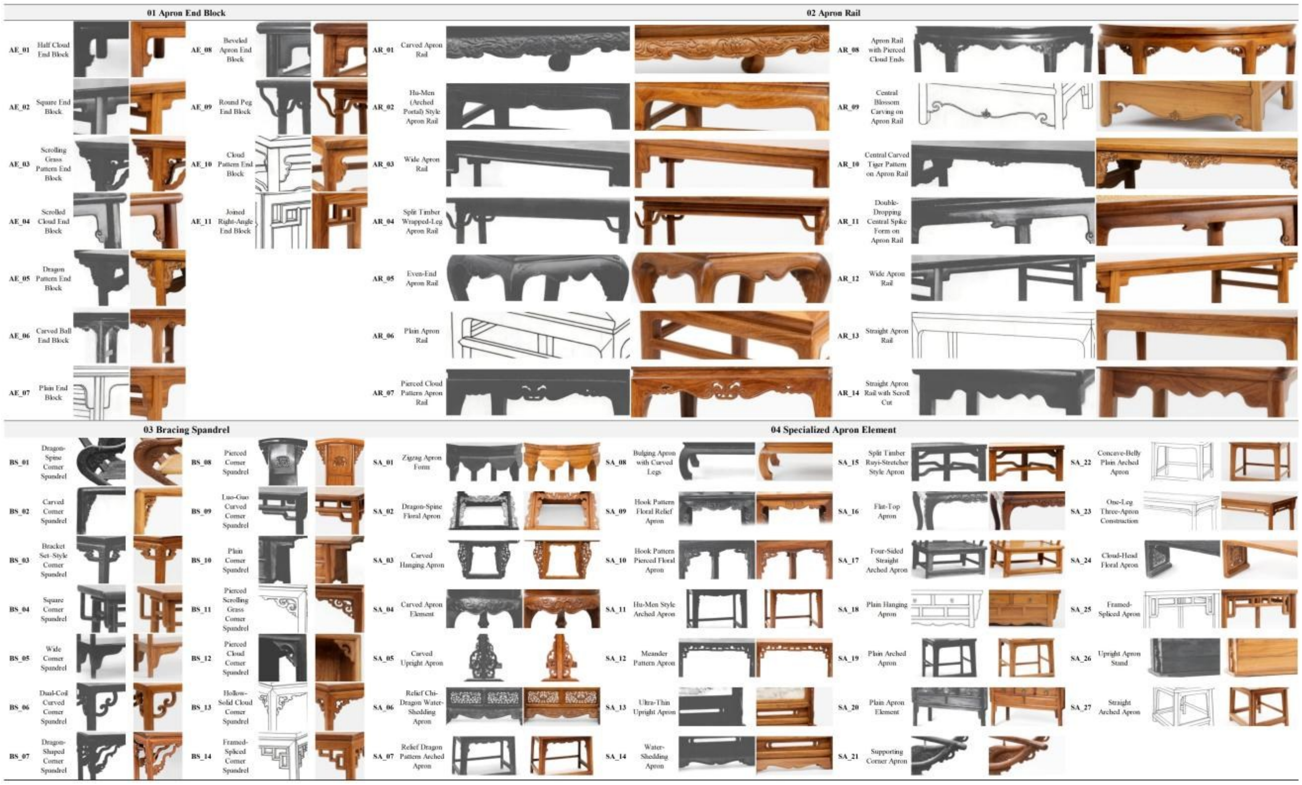

Fig. 7. Comparison of reconstructed images of 66 types of wooden bracket components in Ming-Style furniture

Experiment 2: CMF Redesign Experiment (16 Sets of Prompt Semantic Combinations)

After completing the image restoration experiment of Ming-style furniture apron components, to further verify the feasibility of generative AI achieving "from restoration to redesign" under semantic control, this study constructed 16 representative Prompt semantic combination experiments (Table 2). The experimental objectives of this stage were: (1) to explore the perceptual generation rules of the AI model under different CMF semantic prompts; (2) to compare the influence of traditional, trend, and creative material semantics on image output features and cultural expression; (3) to verify the role of the Prompt structure in the controllability and style stability of component-level semantics.

Experimental design ideas and semantic grouping logic

This experiment used the three-dimensional semantic structure of "furniture attribute semantics (F type), component shape semantics (S type), and CMF semantics (M type)" as the core framework (corresponding to the original A, B, and C types), and formed 16 Prompt experimental units (G001 through G016) through systematic combination (Table 2).

Table 2. Experimental Design of CMF Semantic Combinations for Ming-style Yazi Components

Scheme ID	Prompt Code	Combination Formula	A-Class Semantics: Furniture Component Attribute	B-Class Semantics: Structural Morphology	C-Class Semantics: CMF Design Combination Type
G001	EXP01	A01+B01+C01	A01 Ming-style furniture + Stool	B01 Cloud-patterned Yazi-head	C01 Traditional CMF: Huanghuali + Natural wood tone + Carving
G002	EXP02	A02+B02+C01	A02 Ming-style furniture + Table	B02 Curly-grass corner-Yazi	C01 Traditional CMF: Huanghuali + Natural wood tone + Carving
G003	EXP03	A03+B03+C01	A03 Ming-style furniture + Chair	B03 Arched Yazi-beam	C01 Traditional CMF: Huanghuali + Natural wood tone + Carving
G004	EXP04	A04+B03+C01	A04 Ming-style furniture + Armchair	B03 Arched Yazi-beam	C01 Traditional CMF: Huanghuali + Natural wood tone + Carving
G005	EXP05	A02+B02+C02	A02 Ming-style furniture + Table	B02 Curly-grass corner-Yazi	C02 Trend CMF: Recycled wood chips + 3D printing + Off-white matte finish
G006	EXP06	A02+B04+C02	A02 Ming-style furniture + Table	B04 Hu-men (pot-door) Yazi-beam	C02 Trend CMF: Recycled wood chips + 3D printing + Off-white matte finish
G007	EXP07	A01+B01+C03	A01 Ming-style furniture + Stool	B01 Cloud-patterned Yazi-head	C03 Trend CMF: Ceramic particles + Collage pressing + Brick-red mixed texture
G008	EXP08	A02+B02+C03	A02 Ming-style furniture + Table	B02 Curly-grass corner-Yazi	C03 Trend CMF: Ceramic particles + Collage pressing + Brick-red mixed texture
G009	EXP09	A02+B04+C04	A02 Ming-style furniture + Table	B04 Hu-men (pot-door) Yazi-beam	C04 Trend CMF: Recycled plastic + Color flake remolding + Light blue/translucent texture
G010	EXP10	A02+B02+C04	A02 Ming-style furniture + Table	B02 Curly-grass corner-Yazi	C04 Trend CMF: Recycled plastic + Color flake remolding + Light blue/translucent texture
G011	EXP11	A04+B03+C04	A04 Ming-style furniture + Armchair	B03 Arched Yazi-beam	C04 Trend CMF: Recycled plastic + Color flake remolding + Light blue/translucent texture
G012	EXP12	A03+B03+C05	A03_Ming-style furniture + Chair	B03_Arch-shaped apron (Juan-kou style)	C05_Creative CMF Combination 1: Bamboo material + Green silk textile embellishment + Phoenix embroidery craftsmanship
G013	EXP13	A04+B04+C05	A04_Ming-style furniture + Armchair	B04_Plain apron (Su-ya style)	C05_Creative CMF Combination 1: Bamboo material + Green silk textile embellishment + Phoenix embroidery craftsmanship
G014	EXP14	A05+B05+C06	A05_Ming-style furniture + Portable box	B05_Small stepped apron (Xiaozhan style)	C06_Creative CMF Combination 2: Iridescent acrylic material + Peony floral elements + Openwork carving craftsmanship
G015	EXP15	A05+B05+C05	A05_Ming-style furniture + Portable box	B05_Small stepped apron (Xiaozhan style)	C05_Creative CMF Combination 1: Bamboo material + Green silk textile embellishment + Phoenix embroidery craftsmanship
G016	EXP16	A04+B04+C06	A04_Ming-style furniture + Armchair	B04_Plain apron (Su-ya style)	C06_Creative CMF Combination 2: Iridescent acrylic material + Peony floral elements + Openwork carving craftsmanship

The F-class semantics define furniture categories (such as stools, tables, chairs, armchairs, and carrying boxes), the S-class semantics control the shape of the apron components (such as cloud-patterned aprons, arched aprons, pot-shaped aprons, and small standing aprons), and the M-class semantics cover three major CMF types. The traditional CMF semantic group (C01) focuses on the use of traditional materials and techniques. These include rosewood, natural wood colour, and carving. Trend CMF semantic group (C02 – C04) uses new materials, such as recycled wood chips, ceramic particles, and recycled plastics. This highlights the importance of sustainability and creativity in the process. The Creative CMF semantic group (C05-C06) combines natural materials with oriental decorative elements (such as bamboo and phoenix embroidery) or modern visual materials (such as colourful acrylic and open-work carving). This helps people understand the relationship between cultural symbols and modern art.

This three-dimensional semantic framework design makes each combination of prompts both similar and different in meaning, allowing for a systematic examination of how generative AI responds to different materials, colours, and types of craftsmanship.

Prompt construction and generation process

All experiments were performed on the Dreamina AI platform, with the reference image ratio uniformly set at 80% (based on the optimal parameters determined in the pre-experiments in Section 4.1). The Prompt syntax structure remained consistent, with the input template as follows:

Prompts = [Reference image 80%] + [Ming-style furniture + F-class semantics] + [Yazi + S-class semantics] + [CMF description + M-class semantics] + [white background, high-resolution, single-object view]

While it was running, each prompt generated three image samples, for a total of 48. All the settings for making the samples stayed the same (CFG Scale = 7, steps = 40, resolution = 1024×1024). Next, the research team examined images that clearly showed what they were looking for, such as complete parts and transparent textures. These were chosen as the standard samples for later visual analysis and expert scoring.

Visual observation and preliminary pattern exploration

By comparing and analysing the results of 16 generative experiments, significant differences in the visual responses of generative AI under CMF semantic control can be observed (Fig. 8). First, the traditional CMF semantic group (G001–G004): The results of this project had a steady style. They were the right proportions for each other. Each part of the furniture was made the same way as Ming-style furniture, with nice wood grains and details. The colours were warm and natural. All of these things show that the project was true to its cultural roots and that the style was consistent. For example, the C02 (recycled wood chips + 3D printing) result exhibited a delicate matte finish; C03 (ceramic particles + collage pressing) had a firm hand-painted texture; while C04 (recycled plastic + coloured shavings remoulding) brought a light, contemporary aesthetic effect through its pale blue and semi-transparent texture. However, some samples in this group exhibited semantic drift, such as the “over-glossing” of apron details, reflecting AI’s limitations in interpreting the semantics of complex materials. Finally, the Creative CMF Semantic Group (G012–G016) exhibited the strongest cultural integration characteristics and innovative potential. The C05 result (bamboo + silk embroidery + phoenix embroidery) exhibited a natural texture and an oriental charm, with precise details and a lustrous sheen in the embroidery. C06 (vibrant acrylic + openwork carving) can be described as visually highly modern, with transparent layering and high-gloss reflections giving the work a strong sense of space. However, its harmony with the traditional Ming-style context was slightly lower. This indicated that the prompt structure effectively guided the generative AI to produce visual innovation semantics. However, the generated results still showed limited consistency in preserving traditional Ming-style cultural semantics.

Fig. 8. Comparison of 16 different types of semantic group generation results

The results of the complete observation indicate that generative AI's responses to CMF semantics exhibited hierarchical structure. First, it represented traditional meanings in a way that was able to be reproduced and was stable. Second, it represented trend meanings in a more innovative and visually exploratory way. Moreover, third, it represented creative meanings in a way that shows the potential for combining cultural symbols and transferring meanings.

This pattern indicates that the Prompt structure not only can effectively guide AI's semantic generation at the material and process levels, but also achieve a gradual transition from "cultural restoration" to "creative reconstruction." The results of AI-generated content exhibit three typical patterns. First, the restorative pattern, represented by C01, emphasises historical authenticity in terms of form and craftsmanship. Second, the integrative pattern, represented by C02–C05, balances cultural heritage with modernity. Third, the experimental pattern, represented by C06, pursues visual innovation and cross-media aesthetic expression. From the perspective of cultural heritage redesign, the C05 (bamboo + phoenix embroidery) and C04 (recycled plastic + chroma remoulding) schemes are the most representative: the former strengthens the cultural coherence of "New Chinese" aesthetics at the semantic level, while the latter represents the contemporary expression of sustainable material semantics. Both demonstrate that AI not only can reproduce the semantics of traditional crafts but also achieve a dynamic balance between cultural cognition and innovative design through Prompt control.

In summary, the 16 CMF redesign experiments validated the material perception, style adaptation, and cultural extension capabilities of generative AI under semantic control. Guided by the Prompt structure, the AI model can achieve semantic transfer from traditional restoration to innovative redesign, providing a solid empirical foundation for subsequent chapters on user perception, significant difference analysis, and redesign path optimisation.

Experimental Summary

The experimental results in this chapter fully validate the potential of generative artificial intelligence in image generation and redesign driven by the semantics of traditional furniture, revealing the key role and influence mechanism of Prompt semantic control in the visualisation of cultural heritage. Overall, the conclusions can be summarised in three aspects:

First, the experiment confirmed that Semantic-Driven worked well. By using semantic limits and ways to control reference images when restoring Ming-style furniture apron components, the results showed that the structure and style remained very similar to the original. The AI-generated image mostly matched the form and craftsmanship of the reference image when the reference image weight was set to 80%. It also kept the exact proportions and decorative logic of the original components. This result shows that controlling the semantic hierarchy and parameter weights together is an important part of making sure the quality of AI image restoration is good. It also provides a technical reference for the digital restoration of traditional crafts.

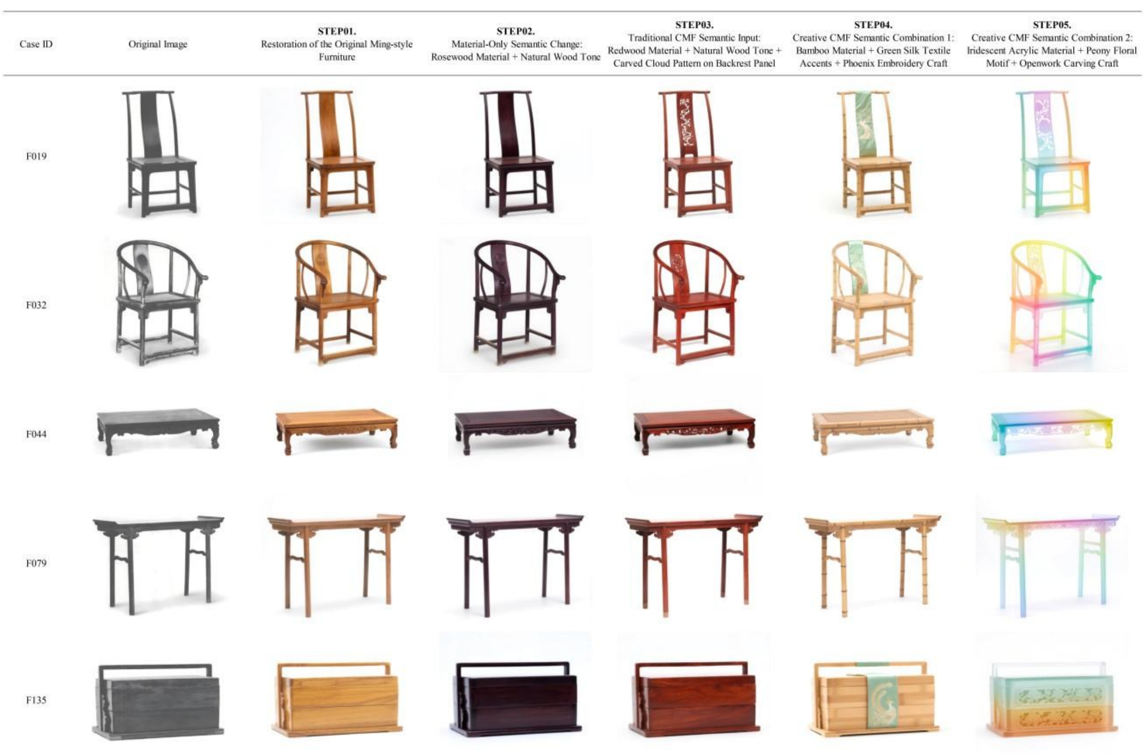

Fig. 9. Comparison of generation results for different CMF semantic groups

Second, CMF semantic variables had a role in expressing innovation in culture. In the redesign experiment, different combinations of materials and how they are made had a big effect on how the AI-generated images looked and what they meant to the culture.

Traditional groups of words (such as "rosewood + carving") show great stylistic continuity and fidelity. On the other hand, groups of words that are driven by trends (such as "recycled plastic + remoulding process + transparent colored texture") and groups of words that are creative (such as "bamboo + silk weaving + phoenix embroidery") show a stronger sense of modernity and cultural reinterpration (Fig. 9). The combination of bamboo and silk embroidery in particular strikes a balance between traditional and contemporary styles. This shows that designing at the semantic level can help guide generative AI towards two important goals: "cultural continuity" and "innovative expression."

Finally, the way the Prompt structure can be transferred creates new possibilities for generating culture in different areas. The semantic template design method proposed in this study can be used with different components and styles. This suggests that AI can create new types of content within a clear semantic framework. This feature paves the way for future image reconstruction, style transfer, and intelligent redesign of cultural heritage. It also provides a reference for constructing an integrated "semantic-generative-perception" model for design practice. In summary, this chapter used a systematic experiment with two stages—restoration and redesign—to show that generative AI can be trusted and is flexible when it comes to the meaning of the apron parts of Ming-style furniture. It shows that AI can accurately recreate traditional design languages and has the ability to create new cultural designs. This conclusion provides a solid theoretical and experimental foundation for the quantitative analysis, expert perception evaluation, and discussion of cultural semantic mechanisms in the chapters that follow.

Expert Scoring Results and Statistical Feature Analysis

To systematically evaluate the performance of generative AI in restoration and redesign under semantic control, this study invited 18 experts and scholars from the fields of design, artificial intelligence, materials science, and cultural heritage protection to conduct multidimensional subjective scoring of all image results generated in the previous section. The scoring system included four core indicator dimensions: (A) Ming-style furniture restoration accuracy; (B) Chinese aesthetic expression; (C) Functional and practical expression; and (D) CMF (Colour, Material, Finish) integration innovation. All experts conducted independent evaluations based on a 5-point scale (1 = very low, 5 = very high), ultimately generating 288 sets of valid scoring data. After standardisation, the scoring results were analysed using SPSS and Excel for descriptive statistics and variance testing. The relevant results are shown in Table 3.

Table 3. Descriptive Statistics of Four Evaluation Dimensions

Dimension	Sample Size (n)	Minimum	Maximum	Mean	Standard Deviation (SD)	Median
Restoration fidelity of Ming-style furniture	288	1	5	4.017	0.897	4
Aesthetic performance of Chinese style	288	1	5	4.024	0.931	4
Functional and practical expression	288	2	5	4.031	0.861	4
CMF integration and innovativeness	288	1	5	4.035	0.921	4
* Values are derived from expert evaluations (N = 288, 18 experts × 16 groups). Ratings were based on a five-point Likert scale (1 = very low, 5 = very high).						

Descriptive statistics show that the average scores across all four core evaluation dimensions were above 4.0 (4.017 to 4.035), indicating that experts generally recognised generative AI's performance in restoration and redesign under semantic control. Among them, "CMF Integration Innovation" scored the highest (M = 4.035), indicating that the AI possesses strong creative generation capabilities under the synergistic effect of color, material, and process semantics; "Functional and Practical Expression" scored the second highest (M = 4.031), suggesting that the generated results also have good readability and design rationality in terms of structure and functional logic.

The standard deviations for each dimension ranged from 0.861 to 0.931. There was a slight variation in the results. This shows that the experts' scores were consistent. "Functional Expression" had the lowest dispersion (SD = 0.861), which indicates that the judges agreed the most on what they were looking for. In contrast, "Chinese Aesthetic Expression"had a slightly higher standard deviation (SD = 0.931), reflecting subjective differences in cultural aesthetic understanding. Here, "Chinese Aesthetic Expression" was operationalized as the extent to which the generated image conveys recognizable Ming-style aesthetic cues — such as overall style coherence, proportion and line quality, appropriateness of cultural/ornamental semantics, and visual harmony. The median for all scores was 4, with extreme values ranging from 1 to 5. Only the "functional expression" score had a minimum of 2, indicating a high concentration of scores and no significant skewness.

Overall, the AI achieved a good balance across the four dimensions—structural fidelity, aesthetic reproduction, functional presentation, and CMF innovation — demonstrating the stability and adaptability of the semantic control mechanism in complex cultural contexts. It is interesting to note that changes in the aesthetic dimension suggest that future models can improve the cultural meaning and style consistency. On the other hand, the excellent performance in the CMF dimension shows that Prompt design has the potential to shape perceptions of materials and drive visual innovation. In conclusion, the AI generation system demonstrates strong overall performance across multiple objectives—fidelity, aesthetics, functionality, and innovation—and provides an effective experimental basis for the semantic restoration and contemporary expression of traditional furniture.

Between-group Comparison under Different Semantic Experimental Groups

This section compares the same four evaluation dimensions (A–D) across three semantic experimental groups (traditional, CMF-trend, and creative CMF) rather than introducing new evaluation criteria.

Traditional semantic group: comparative results across the four evaluation dimensions

In the first phase of the experiment, the semantic CMF (Huanghuali wood) cues C01 (Huanghuali wood + natural wood colour + carving) were fixed. Four different furniture categories and Yazi component shapes (G001–G004) were used as variables to explore the structural fidelity and stylistic stability of generative AI in the image restoration of Ming-style furniture under traditional semantic conditions. According to Table 4-2, the four semantic combinations specifically included: G001: Stool × Cloud-patterned apron; G002: Table × Scroll-patterned corner apron; G003: Chair × Curved apron; and G004: Armchair × Curved apron.

These combinations together make up a typical Ming-style furniture design system. This system includes various components, from small pieces to seating. It shows how stable designs can be when there are specific rules about what they mean. In addition, a total of 18 experts from the fields of design, materials and cultural heritage participated in the scoring, using a 5-point scale to evaluate four dimensions: Ming-style furniture reproduction (A), Chinese aesthetic expression (B), functional and practical expression (C) and CMF integration innovation (D).

Table 4. Mean Scores of Each Dimension in the Traditional Semantic Group (G001–G004, n = 18)

Dimension	G001	G002	G003	G004	F-value	p-value	η^2
Restoration fidelity (A)	4.44 ± 0.51	4.33 ± 0.59	4.39 ± 0.50	4.33 ± 0.62	0.102	0.958	0.006
Chinese aesthetic performance (B)	4.17 ± 0.67	4.33 ± 0.61	4.06 ± 0.66	4.33 ± 0.60	0.231	0.875	0.011
Functional and practical expression (C)	4.39 ± 0.58	4.11 ± 0.63	4.39 ± 0.58	4.28 ± 0.56	0.184	0.906	0.009
CMF integration and innovativeness (D)	3.39 ± 0.63	3.44 ± 0.59	3.44 ± 0.61	3.56 ± 0.67	0.203	0.893	0.010

* η^2 represents the partial eta-squared effect size. No significant differences were found among the four traditional semantic groups ($p > 0.05$).

Table 4 shows that the mean values of the four core evaluation dimensions were all at a high level (3.39 to 4.44), and the standard deviations were low (0.50 to 0.67), indicating that under unified semantic constraints, the generative AI's image output is generally stable, the scores are concentrated, and the expert opinions are consistent.

In the dimension of "Ming-style furniture reproduction (A)," the AI performed best in component shape recognition and structural reproduction, especially for the G001 and G003 samples, which had the highest structural fidelity, with line proportions and mortise-and-tenon logic conforming to traditional craftsmanship standards. "Functionality and practicality expression (C)" was the second highest, indicating that the generated results not only had visual reproduction capabilities but also retained the functional logic of furniture components well, such as the supporting structure and scale relationship.

The score for the "Chinese aesthetic expression (B)" dimension stayed the same (4.06 to 4.33), which means that the model kept a strong style consistent under conditions where all the words mean the same thing. Although there were slight changes in the details, there was no overall change in style. In contrast, the "CMF Integration Innovation (D)" score was the lowest (3.39 to 3.56), reflecting that the AI tended to conservatively reproduce rather than actively reconstruct under traditional material cues, consistent with the restoration orientation set by the highly consistent semantics of "Huanghuali + Carving".

The ANOVA results further validated this trend. The F-values for all four dimensions were low (0.102 to 0.231), the p-values were all greater than 0.05 (0.875 to 0.958), and the η^2 value was less than 0.01, indicating that different furniture categories and component shapes had little impact on the score. This result demonstrates the stabilising effect of the semantic constraint mechanism in the generation process, particularly prominent in the structural and aesthetic dimensions.

When the CMF semantics (Huanghuali, natural wood colour, carving) were mechanically fixed, they created a strong style that stayed the same throughout diffusion. This kept the image from changing and made sure that the model continued to represent itself the way Ming-style furniture is usually shown over time. The key benefit of Prompt-based semantic control generation is that it maintains the structure and style.

In summary, the traditional semantic group (C01) experiment verified the strong positive correlation between semantic consistency and generation stability. The AI model can achieve high-fidelity, high-consistency image restoration with fixed semantic input, providing an important baseline for comparative analysis of trend and creative semantic groups and laying the foundation for building an interpretable, reproducible cultural image generation system.

CMF trend semantic group: comparative results across the four evaluation dimensions

In the second phase of the experiment, the study systematically generated and compared images for three representative CMF design trend semantics (C02, C03, and C04), aiming to explore the impact of material and process semantic changes on the perceptual performance of AI-generated images. Specifically, C02: recycled wood chips + 3D printing process + off-white matte texture (G005: table × scrollwork corner braces; G006: table × jar-shaped apron); C03: ceramic particles + collage pressing process + brick red mixed texture (G007: stool × cloud-patterned apron; G008: table × scrollwork corner braces); C04: recycled plastic + colored chip remolding process + light blue/transparent colored texture (G009: table × jar-shaped apron; G010: table × scrollwork corner braces; G011: armchair × arched apron). This phase of the experiment covered a continuous semantic gradient from natural materials to composite materials, aiming to verify the adaptability and stability of the AI model within the traditional-contemporary CMF semantic continuum. As shown in Table 5, the average scores of the seven groups of samples were generally medium-high (3.50–4.78), indicating good generation quality and high consistency.

Table 5. Descriptive Statistics of the CMF Trend Semantic Groups (Mean ± SD, n = 18)

Group	Restoration fidelity	Chinese aesthetic performance	Functional and practical expression	CMF integration and innovativeness
G005	3.61 ± 0.84	3.94 ± 0.89	4.11 ± 0.67	4.11 ± 0.73
G006	3.61 ± 0.83	3.72 ± 0.78	4.17 ± 0.61	4.00 ± 0.67
G007	3.83 ± 0.82	4.00 ± 0.73	4.28 ± 0.63	4.11 ± 0.62
G008	4.11 ± 0.78	4.22 ± 0.67	4.17 ± 0.54	4.28 ± 0.57
G009	3.50 ± 0.86	3.83 ± 0.74	3.56 ± 0.69	4.61 ± 0.49
G010	3.61 ± 0.90	3.78 ± 0.80	3.78 ± 0.73	4.67 ± 0.45
G011	4.06 ± 0.79	4.17 ± 0.69	4.22 ± 0.63	4.78 ± 0.42

In the category of "Ming-style furniture reproduction (A)," G008 (4.11 ± 0.78) and G011 (4.06 ± 0.79) scored high, showing that the natural materials (like ceramic particles and wood surfaces) or warm textures (like metal-plastic combinations) help keep the structure and proportions of the original piece. Conversely, G005 and G009 scored relatively low (3.50 to 3.61), suggesting that some material semantics (such as matte grey and remoulded particles) may interfere with component boundary recognition. Although the ANOVA results ($F = 2.43$, $p = 0.064$, $\eta^2 = 0.058$) were not significant, they did show a trend.

In the dimension of "Chinese aesthetic expressiveness (B)," the scores were stable (3.72 to 4.22), with both G008 and G011 groups showing outstanding performance, indicating that warm colours and delicate texture semantics were more conducive to generating Chinese-style images. The ANOVA results ($F = 2.15$, $p = 0.079$) were marginally significant, and the Tukey test showed that G008 was significantly higher than G005 ($p < 0.05$), indicating that the optical properties and colour temperature of the material have a preliminary impact on aesthetic perception.

The "Functionality and Usability Expression (C)" dimension scored relatively high (3.56 to 4.28). However, the differences were not significant ($F = 1.28$, $p = 0.262$), indicating that the model was able to identify and express the functional logic of components under different CMF semantics. This result was consistent with the traditional semantic group, verifying the stability and interpretability of AI at the level of structure generation.

The results showed that there were significant differences in the "CMF Integration Innovation (D)" dimension ($F = 3.97$, $p = 0.012$, $\eta^2 = 0.062$), see Table 6. Tukey's test results showed that groups G009 and G010 performed much better than groups G005 and G006 ($p < 0.05$). This indicates that using modern CMF semantics (such as recycled and reclaimed plastic scraps) can boost the ability to generate new ideas. These semantics include complex optical properties (high reflectivity, translucency, and high-saturation colours), enhancing the model's expressive potential for texture mapping and material reconstruction layers. Group G011 (4.78 ± 0.42) maintained a high level under semantic transfer conditions, reflecting that the AI has good semantic transfer stability and CMF adaptability.

Table 6. Results of RM-ANOVA and Tukey Post-hoc Tests

Evaluation Dimension	F	p	η²	Significant Between-group Differences (Tukey HSD)
Restoration fidelity	2.43	0.064	0.058	No significant difference ($p > 0.05$)
Chinese aesthetic performance	2.15	0.079	0.051	G008 > G005 (marginally significant)
Functional and practical expression	1.28	0.262	0.027	No significant difference
CMF integration and innovativeness	3.97	0.012	0.062	G009, G010 > G005, G006 ($p < 0.05$)
*Significance levels: *p < 0.05, *p < 0.01. η² represents the effect size (partial eta-squared).				

Overall, the CMF trend semantic group experiment showed that more complex words led to better performance. As material semantics changed from natural wood to composite or recycled materials, AI-generated images evolved from "conservative restoration" to "semantic reconstruction." The model showed significant improvements in "aesthetic expressiveness" and "CMF innovation," while maintaining "structural stability" and "functional integrity" (C). This demonstrates the model's ability to produce a variety of results based on its semantic-driven generation mechanism.

These results show that generative AI can express new ideas in a way that respects cultural symbols. It can do this by using something called "CMF semantic transfer." This helps to move from traditional ideas to modern ones in a balanced way. Furthermore, from a design perspective, this experiment verified the adaptive mechanism of the AI system within the "material-process-culture" triadic semantic framework: when the input semantics contain contemporary design-oriented elements such as "regeneration," "collage," and "reshaping," the model tends to explore new visual language expression paths while maintaining formal stability.

This discovery provides a theoretical foundation for the Creative Semantic Group Experiment (C05 to C06). It also provides a way to achieve a balance between controllability and innovation when redesigning cultural heritage.

Creative CMF semantic group: comparative results across the four evaluation dimensions

In the third phase of the experiment, the research focused on creative CMF semantics (C05–C06) with contemporary expressive characteristics. Through the "Innovative Semantic Combination" experiment (G012–G016), it further verified the creative generation potential and cultural adaptability of generative AI in cross-semantic environments. Specifically, variable C05 (bamboo material + green silk embellishment + phoenix embroidery): G012 (chair × perforated apron); G013 (armchair × plain apron); G015 (box × small perforation); variable C06 (vibrant acrylic + peony element + openwork carving): G014 (box × small perforation); G016 (armchair × plain apron). Variables: The semantics of C05 represent the path of "fusion of natural materials and handicrafts," emphasising the contemporary expression of Eastern imagery and ecological materials; the semantics of C06 lean towards "combination of new materials and decorative art," reflecting modern aesthetic characteristics such as gloss, transparency, and patterned composition.

As can be seen from the descriptive statistics in Table 7, the five groups of samples performed well overall, with the mean ranging from 3.50 to 4.67 and the standard deviation from 0.63 to 1.04, indicating that the overall quality of the generated results was high. However, the fluctuations were slightly larger under the innovative semantics, showing the characteristics of "high creativity - high dispersion".

Table 7. Descriptive Statistics of the Creative Semantic Groups (Mean ± SD, n = 18)

Group	Restoration fidelity	Chinese aesthetic performance	Functional and practical expression	CMF integration and innovativeness
G012	4.22 ± 0.92	4.22 ± 0.89	3.94 ± 0.95	4.33 ± 1.00
G013	4.33 ± 0.85	4.28 ± 0.86	4.06 ± 0.88	4.44 ± 0.89
G014	4.17 ± 0.88	4.39 ± 0.79	4.00 ± 0.84	4.56 ± 0.86
G015	4.56 ± 0.73	4.50 ± 0.63	4.33 ± 0.73	4.67 ± 0.63
G016	3.83 ± 1.04	3.50 ± 0.98	3.89 ± 0.86	4.33 ± 0.96

In the dimension of "Ming-style furniture reproduction accuracy (A)," group G015 scored the highest (4.56 ± 0.73), significantly higher than G016 (3.83 ± 1.04) ($F = 2.73$, $p = 0.037$, $\eta^2 = 0.061$). The results indicate that when the meaning of words was combined with natural materials (such as bamboo) and decorative details (such as phoenix embroidery), the model better balanced the expression of cultural symbols and the accuracy of the structure. On the other hand, highly reflective colours such as iridescent acrylic can make it hard to recognise shapes, which is called the "semantic interference effect."

The difference was most pronounced in the dimension of "Chinese aesthetic expressiveness (B)" ($F = 3.58$, $p = 0.012$, $\eta^2 = 0.075$). Tukey's test showed that G015 was a lot higher than G016 and G012 ($p < 0.05$). This indicates that using a mix of natural materials, handicrafts, and oriental patterns in one image effectively increases the cultural elements and visual order of the image. In particular, the phoenix embroidery element enhanced the expressive effect of "oriental aesthetic logic" in terms of detail, rhythm and overall composition.

The "functionality and practicality expression (C)" dimension remained stable overall (3.89–4.33), with no significant difference ($F = 1.96$, $p = 0.106$), indicating that the AI system was able to still maintain an accurate understanding of the function and structure of components under complex semantic conditions, without compromising structural rationality due to creative prompts.

The "CMF integration innovation (D)" dimension showed the biggest difference ($F = 4.14$, $p = 0.007$, $\eta^2 = 0.083$). Tukey's test showed that G015 performed much better than G012, G013, and G016 ($p < 0.05$) (Table 8). This shows that G015 was the most innovative in terms of colour, material, and craftsmanship. The way it mixed and matched "bamboo + phoenix embroidery + box structure" got the model's creative juices flowing. They were able to come up with new textures and shapes that turned traditional ideas into modern ones. In contrast, C06's vibrant acrylic and openwork had a modern feel, but its structure and appearance were slightly less consistent. This suggests that AI still has technical challenges in recognising boundaries when dealing with transparent materials and complex lighting.

Table 8. Results of RM-ANOVA and Tukey Post-hoc Tests

Evaluation Dimension	F	p	η²	Significant Between-group Differences (Tukey HSD)
Restoration fidelity	2.73	0.037 *	0.061	G015 > G016 (p < 0.05)
Chinese aesthetic performance	3.58	0.012 **	0.075	G015 > G016, G012 (p < 0.05)
Functional and practical expression	1.96	0.106	0.043	No significant difference
CMF integration and innovativeness	4.14	0.007 **	0.083	G015 > G012, G013, G016 (p < 0.05)
* Significance levels: *p < 0.05, *p < 0.01. η² represents the effect size (partial eta-squared).				

Comprehensive analysis showed that C05 and C06 represent two paths in AI generation, transitioning from "trend imitation" to "semantic innovation." The C05 (bamboo + embroidery) piece showed how cultural symbols and material images worked together. It created images that mixed Eastern designs with ecological designs. This shows how culture can adapt to new environments and be expressive and new. C06 (acrylic with open areas), however, demonstrates both the difficulties and possibilities of using high reflectivity and complex textures in creating models. While it makes things look better, it makes the structure less accurate.

From the perspective of generation mechanisms, the innovative semantic group experiments validated AI's "dual-channel response mechanism" in semantic level transitions: on the one hand, maintaining morphological stability and cultural logic through semantic coherence; on the other hand, achieving style reorganisation and material innovation at the CMF level through semantic divergence. G015's comprehensive leadership across all four dimensions reflects the optimal expression point of "fidelity-innovation" bidirectional balance under this mechanism.

Overall, the results of the Creative CMF Semantic Group indicated that generative AI can achieve high-level semantic innovation within the constraints of cultural context. A comparison of C05 and C06 shows a non-linear relationship between the complexity of the material and its ease of fabrication. As the study moved from natural to artificial composite materials, the stability of the generated structure decreased slightly, while visual innovation improved significantly. This experimental phase not only verified the controllability and cultural sensitivity of semantic-driven mechanisms in complex generative tasks but also provided a methodological basis and quantitative reference path for traditional furniture to move from semantic restoration to contemporary expression.

Overall comparison and discussion of statistical significance

To understand how the order of words in a phrase affects the quality and cultural expression capabilities of AI-generated images, this study compared the results of three experiments. The first experiment was a traditional semantic group (G001 to G004). The second experiment was a trend semantic group (G005 to G011). The third experiment was an innovative semantic group (G012 to G016). By calculating the overall mean and standard deviation of four core evaluation dimensions (Ming-style furniture reproduction accuracy, Chinese aesthetic expression, functional and practical expression, and CMF integration innovation), and combining one-way ANOVA and Tukey post-hoc tests, the study clarified the performance patterns and significant differences of different semantic types in the generated results.

Overall, the average scores of each semantic group across the four evaluation dimensions remained at a medium-to-high level ($M = 4.01$ to 4.46), demonstrating that the AI system possesses high image generation capabilities and semantic consistency under semantic control. The "Ming-style furniture reproduction accuracy" dimension showed the smallest difference among the three semantic groups, indicating that regardless of the complexity of the semantic input, the AI can maintain the structural proportions and morphological outlines, demonstrating a strong ability to recognise form and a style constraint effect. The "CMF integration innovation" category was the most different between the groups ($F = 5.12$, $p < 0.01$, $\eta^2 = 0.091$). Thus, the way people understand AI-generated images and how creative they are is affected by the material and craftsmanship.

To compare the impact of different semantic levels on the AI image generation performance, this study summarised and analysed the scores of three semantic groups (traditional, trending, and innovative) across four evaluation dimensions. Figure 10 shows the radar distribution of the mean scores for each group. All dimensions had mean scores above 4.0, indicating that the AI model generated high-quality images with semantic cues.

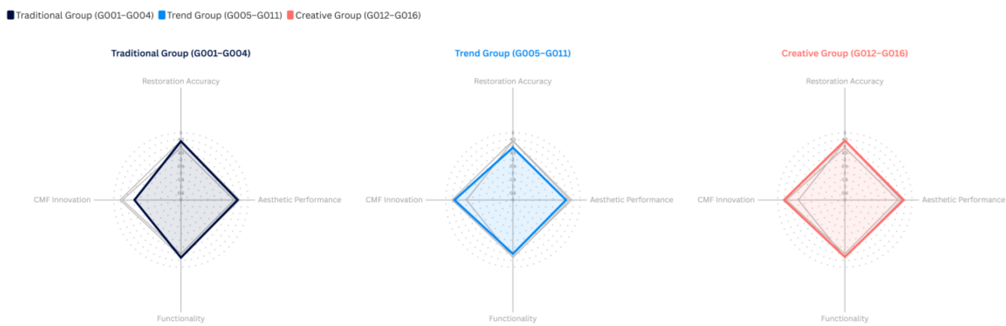

Fig. 10. Radar chart of the overall mean scores across four evaluation dimensions for the three semantic groups

Among them, “Ming-style furniture reproduction accuracy” showed the smallest difference among the three groups, indicating strong structural stability and resistance to semantic complexity. However, “CMF integration innovation” showed the most significant difference ($F = 5.12$, $p < 0.01$), indicating that material and craftsmanship semantics played a decisive role in the generated performance.

The traditional semantic group remained the same in how it is structured and how it works, which highlights the “replicative generation” characteristic. The trending semantic group made it easier to express new ideas by using different types of materials, especially materials that have been recycled. This made it a lot better to show what something looks like. The innovative semantic group got the highest scores in the aesthetics and CMF dimensions. This shows that the AI can work with people to create culture using complex semantic cues.

Tukey’s test further confirmed that the innovation group significantly outperformed other groups in both “CMF integration innovation” and “Chinese aesthetic expression” ($p < 0.05$), while there was no significant difference in the “functional and practical expression” dimension, indicating that the AI has good stability in structural understanding.

From a mechanistic perspective, the differences in generation results induced by different semantic levels reflected the cultural adaptability mechanism of the AI model: under traditional semantic input, the model exhibited high stylistic consistency and visual stability; under trend semantic conditions, material semantic transfer activated the expressiveness of texture generation and light perception changes; and under the drive of innovative semantics, the model achieved the re-encoding and contemporary translation of cultural symbols, thus completing the generative leap from “imitative restoration” to “semantic co-creation.” These three types of semantic combinations, starting with simple concepts and progressing to complex ones, show how AI image generation systems can create new things within traditional cultural contexts, demonstrating the creative potential of AI.

LIMITATIONS

Although this study has demonstrated the feasibility of generative AI in the two-dimensional image restoration and CMF semantic redesign of Ming-style furniture brackets, the following limitations remain.

First, this study primarily focuses on 2D image generation and visual evaluation. Its objective was to validate the potential of generative AI for image restoration and the conceptual redesign of traditional components, rather than 3D modelling, structural reconstruction, or design expressions for engineering manufacturing. Therefore, the current method does not yet support multi-view presentation, 3D reconstruction, or a comprehensive spatial understanding of furniture components.

Second, the Jiemeng AI platform used in this study is a commercial black-box generative system. This paper explored the relationships among the prompts used, the reference-image control, and the resulting outputs. It did not discuss how the model is trained internally. Consequently, this study does not assume the platform explicitly possesses the ability to reason about perspective, physical properties, or lighting rules; rather, the relevant visual effects are better understood as statistical representations learned by the model from large-scale image data.

Third, the study was evaluated based on how experts saw it. They looked at whether it is accurate, how it looks, how it works, and new ideas in CMF. While this method works for evaluating how well cultural semantic restoration and visual redesign are working, it does not yet address engineering-level validations, such as feasibility, manufacturability, and material performance. This study is better suited to an exploratory experiment on the semantic-controlled generation of traditional craft components than to a comprehensive technical implementation plan.

Finally, the fact that some of the generated results were misinterpreted suggests that the current platform still struggles to understand complex components and cultural meanings. In future work, researchers could also try to add geometric and physical property limits, and rules about lighting. This would make the results more rational, controllable, and easy to understand.

CONCLUSIONS

1. This study confirmed that generative artificial intelligence (using the Dreamina AI platform) can be used to reconstruct images and redesign the way traditional Ming-style furniture components are arranged. By setting the reference image to account for 80% of the overall outline, the results showed that the generative model was excellent in terms of structural fidelity and consistency with traditional style, possessing outstanding image clarity and cultural restoration capabilities, and effectively restoring the outline shape and texture features of wooden components.
2. In the material semantic control experiment, combinations of different color-material-finish (CMF) prompts were tested and then looked at closely to see what they did. The results showed that combinations of words and ideas such as “bamboo + green silk + phoenix embroidery” performed best in visual aesthetics, cultural expression, and expert scoring. In particular, the ecologically renewable properties of bamboo and its cultural symbolism in traditional woodworking received high recognition from experts in materials and woodworking techniques, demonstrating the significant advantages of generative AI in semantic construction for natural materials.
3. This study constructed a three-level Prompt-structured framework for “semantic-driven AI image restoration and redesign,” integrating furniture category, component form, and CMF semantics. A corresponding four-dimensional perception evaluation system based on expert assessment was also developed, quantifying the cultural adaptability and redesign potential of AI image outputs across four dimensions: fidelity, aesthetic

expression, functionality, and CMF innovation. Overall, the expert panel generally recognized the generated results as effective in supporting semantic restoration and CMF-oriented redesign. This method demonstrates good operability, repeatability, and cross-project applicability.

4. To sum it up, this research makes it possible to use generative AI in more situations to restore wooden furniture and bamboo-based components digitally. It also provides a theoretical basis and methodological reference points to promote sustainable design innovation in cultural heritage. This method can provide a concrete path for the future ecological reuse and digital inheritance practices of cultural woodwork.

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