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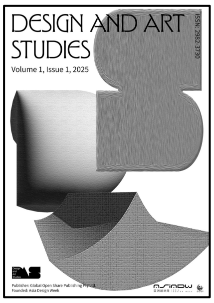

Research Article

A Design Method for Automotive Interior Textures Based on Cultural Semantic Modeling and Generative Design

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Abstract

This study proposes a methodological framework for automotive interior texture design that integrates cultural semantic modeling with generative design techniques. The approach involves collecting relevant cultural imagery materials, extracting high-frequency cultural imagery vocabulary, and constructing a cultural semantic network through keyword co-occurrence analysis. In the semantic modeling phase, the "Entity–Event–Context" paradigm of the CIDOC CRM model is adopted to structurally represent representative cultural elements, thereby forming a semantic model with contextual association capabilities. A semantic-to-design mapping matrix is then established to translate cultural semantics into controllable design prompts. Finally, with the aid of generative design tools such as diffusion models, the semantic information is transformed into interior texture patterns that embody both cultural connotation and visual aesthetics. A design practice based on Han culture demonstrates that this method effectively enhances the cultural expressiveness and emotional recognizability of automotive interior design, offering a feasible path for culture-driven intelligent design.

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1. Introduction

As Electric Vehicles continue to advance rapidly, there is a growing emphasis on addressing the emotional needs of consumers in automotive design. Automotives are no longer merely transportation tools, but lifestyle carriers that reflect identity, aesthetic preferences, and cultural affiliation. In today's highly homogenized automotive market, traditional interior design approaches—often guided by functionality, safety, and material cost—are insufficient to meet users' growing expectations for personalized, aesthetic, and culturally enriched experiences. This is especially true in the mid- to high-end market, where users demand higher standards in design quality, cultural depth, and emotional value. Against this backdrop, cultural creativity is emerging as a key driver for differentiated interior design and the redefinition of brand value.

In recent years, the field of cultural heritage and creative product design has increasingly adopted Semantic Web technologies to organize information and address interoperability issues (Moraitou et al., 2022). Through modeling and structural analysis of cultural semantics, designers can systematically understand the intrinsic relationships among cultural elements and translate them into generative visual languages. This enables a shift in design research from physical symbols to the exploration of deeper semantic structures. Although the integration of cultural elements in automotive interior design has become more prevalent in recent years, practical applications remain limited. In most cases, cultural content is still identified based on designers' subjective judgment, lacking a reliable extraction mechanism and verifiable semantic foundation. There is still no established approach for in-depth semantic modeling of cultural imagery.

Meanwhile, the advancement of artificial intelligence and generative design methods has introduced new tools for the graphical transformation of complex semantics. On one hand, techniques such as semantic encoding and thematic clustering enable the extraction of representative cultural imagery from large-scale textual or visual data, supporting the construction of hierarchical and interpretable semantic networks. On the other hand, by integrating generative design approaches, it becomes possible to achieve a structured "semantic–form–visual" mapping, generating patterns or textures with culturally perceptible features. Although previous studies have demonstrated the feasibility of such methods in fields like fashion design and cultural creative products, their application in automotive interiors remains rare, especially in terms of systematic, controllable, and verifiable research frameworks.

2. Literature Review

2.1. Extraction of Cultural Imagery

Cultural imagery, as a visual representation of cultural values, serves as a crucial medium for cognition, communication, and identity within human societies. Hofstede (1991) defined culture as "the collective programming of the mind which distinguishes the members of one group or category of people from another." From this perspective, images and visual symbols not only carry cultural meaning but also reflect the values and cognitive patterns of specific social groups (Knight et al., 2009). These visual symbols are not static; rather, their symbolic meanings accumulate and evolve over time, interacting dynamically with cultural transmission and transformation.

Although visual imagery enables cross-cultural transmission, its interpretation is deeply shaped by specific cultural contexts. Prior research suggests that while certain themes may be recognizable across cultures, their meanings often shift depending on the design environment, potentially leading to semantic distortion (Chu, 2003). Thus, constructing semantic networks for cultural imagery requires a nuanced understanding of how meaning is produced and perceived within different cultural settings (Su et al., 2020). Generally, cultural imagery can be extracted through two complementary approaches: image-based extraction, which emphasizes the visual reinterpretation of symbols, patterns, and artistic styles (Liang, 2022; Yoo et al., 2021); and text-based extraction, which focuses on semantic analysis of narratives, literature, and discourse to reveal deeper conceptual structures (Inbasekaran et al., 2021; Wu et al., 2024). Together, these methods provide a foundation for culturally grounded semantic modeling in design.

2.2. Cultural Semantic Modeling

Cultural semantic modeling aims to formalize and structure cultural elements for better understanding, preservation, and reinterpretation of cultural knowledge. To address the complexity of cultural representation, Semantic Web technologies and ontology-based approaches have been widely adopted, enhancing interoperability and standardized data management (Moraitou et al., 2022). A key framework in this domain is the CIDOC Conceptual Reference Model (CIDOC CRM), which defines semantic relationships among events, people, artifacts, and time, offering a unified structure for organizing and integrating cultural heritage data across domains (Dörr, 2002). Recent extensions of CIDOC CRM have further enabled region-specific modeling and supported multimodal information fusion and semantic coherence in cultural product design (Bruseker et al., 2017).

To further improve cross-cultural understanding and metaphor interpretation, some researchers have developed hierarchical semantic models tailored to cultural contexts. These models often integrate semantic networks, knowledge graphs, and generative algorithms, embedding information across several layers—such as word-level, attribute-level, perceptual-level, and contextual-level data (Su et al., 2020). Such frameworks enable more precise semantic control and facilitate the visual transformation of abstract cultural concepts into tangible design elements.

2.3. Generative Design Techniques

Generative design is a computational approach that integrates algorithmic logic with predefined objectives to autonomously produce diverse design outputs. With advancements in artificial intelligence, particularly deep learning, generative design has evolved from rule-based geometry generation to data-driven and semantically controlled creation, proving effective across domains such as product form, architecture, and visual patterns. Tools like Text2Mesh (Michel et al., 2022) and Magic3D (Lin et al., 2023) enable the generation of customized 3D models from textual or visual prompts, accelerating iteration and enhancing creative expression.

In cultural design contexts, Artificial Intelligence Generated Content (AIGC) techniques based on Transformer architectures and diffusion models have introduced new possibilities for culturally grounded generative systems. These approaches increasingly incorporate user preferences and perceptual feedback, transitioning from purely data-driven frameworks to perception- and semantics-guided models. For example, Yuan et al. (2024) proposed a generative method for electric vehicle front design tailored to female aesthetic preferences through affective imagery analysis, while Shimomura et al. (2024) integrated the AGE Thinking Model with DCGAN to support sensory evaluation in AI-assisted design.

The design of texture patterns has also benefited significantly from advances in deep generative models, such as Generative Adversarial Networks (GANs) and diffusion-based frameworks. Researchers have increasingly explored how these technologies can be combined with user perception insights to develop more adaptive and responsive systems. Applications span across areas like 3D surface textures (Ma & Chung, 2023; Yin & Song, 2024) and photochromic texture design (Zhu et al., 2024). For example, Xian et al. (2018) studied deep image synthesis guided by elements such as sketch, color, and texture, relying on dedicated texture databases to simulate diverse visual outcomes. More recently, Faruqi et al. (2025) introduced TactStyle, a generative system capable of stylizing 3D models using image input while embedding tactile feedback properties via heightfield-based texture generation.

Recent advances in texture generation have begun to integrate user perception with cultural semantics, offering new opportunities for culture-driven design. However, most existing research still focuses on user perception and style control, and there remains a need to further investigate systematic approaches for embedding cultural semantic structures into the generative mechanism.

2.4. Research Design and Implementation Path

This study focuses on automotive interior texture design and proposes a preliminary methodological framework that integrates cultural semantic modeling with generative design. It aims to explore a systematic path through which cultural imagery can be processed from semantic extraction and structural organization to formal generation. The research first employs citation-based textual analysis and keyword co-occurrence analysis to construct a semantically clear and structurally stable cultural vocabulary and imagery map. A cultural semantic network is then built using semantic encoding and co-occurrence relationships, mapping semantic elements to design attributes. Finally, based on generative logic, the results of semantic clustering are translated into texture generation strategies, enabling the visual expression of cultural imagery.

During the semantic modeling process, we adopt the “Entity–Event–Context” paradigm of the CIDOC CRM model to abstract and hierarchically classify key elements of cultural imagery. Specifically, we collect cultural textual materials and cultural pictorial materials, extracting their representative visual and linguistic symbols as primary semantic units. Based on cultural themes, a multi-level semantic network is constructed, enabling the semantic model to function as an intermediate representation within the texture generation system and support cross-modal mapping from semantics to visuals. The final semantic structure is fed into image generation systems based on Transformer architectures or diffusion models, realizing semantic-driven generation from cultural concepts to automotive interior textures. This study not only expands the methodological system for cultural and creative product design, but also offers a viable path toward intelligent and personalized automotive interior design.

The contributions of this study are twofold:

First, at the theoretical level, it proposes a multi-layered methodological system of “cultural semantics – imagery structure – texture generation”.

Second, at the practical level, it provides automotive manufacturers with a scalable, controllable interior design method that enables both personalization and emotional expression, helping products gain competitive differentiation in a homogenized market.

3. The proposed research framework

To achieve systematic representation and visual generation of cultural semantics in automotive interior texture design, this study constructs a four-stage research framework comprising: Cultural Semantic Extraction, Semantic Extraction and Co-occurrence Network Construction, Semantic Mapping, and Generative Design. This framework begins with the acquisition and encoding of cultural information, progressively builds the corresponding semantic structures, and transforms them into controllable elements that support design generation. Ultimately, cultural expressions are visualized through generative models in the form of texture patterns (see Figure 1).

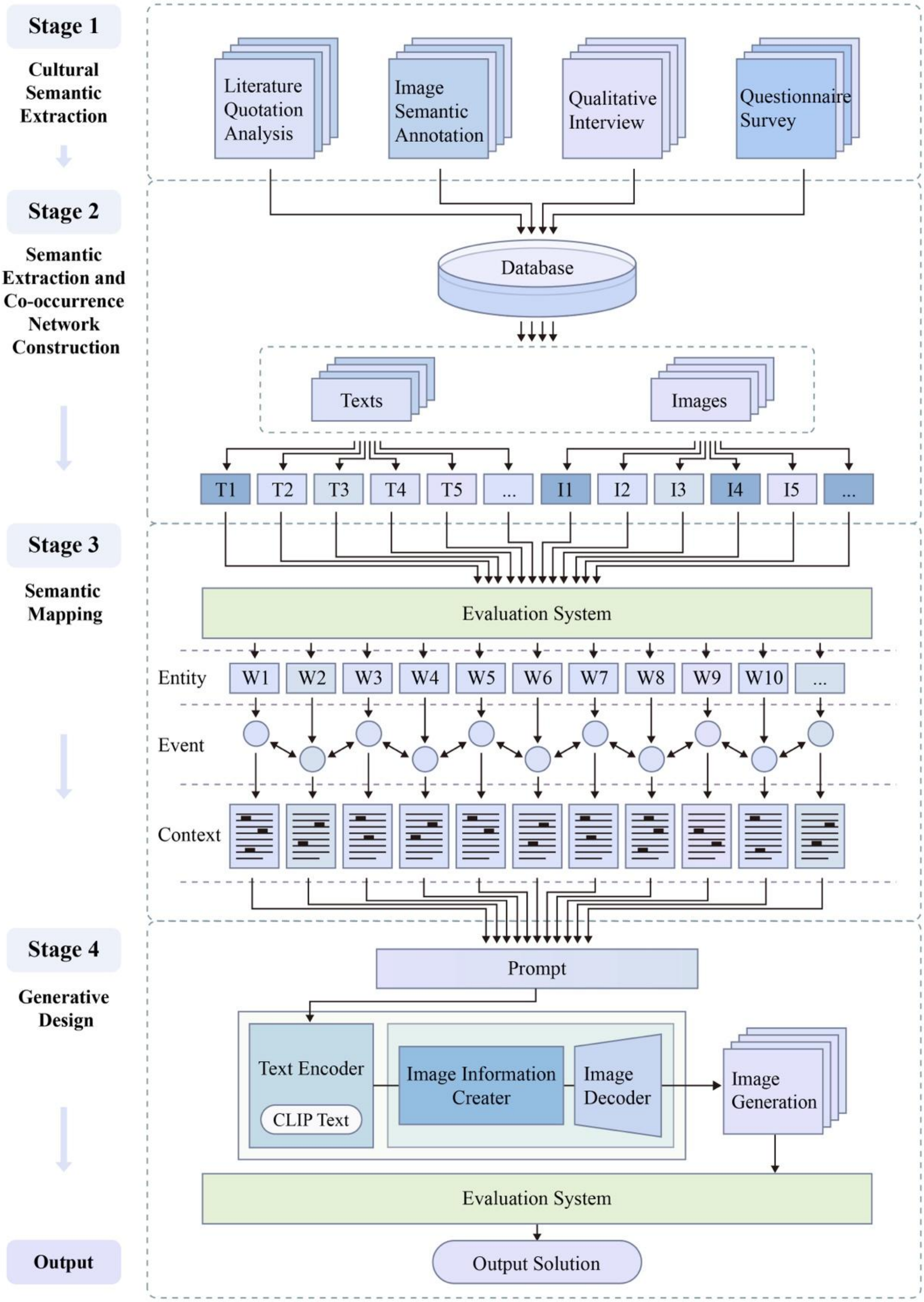

Figure 1. The proposed research framework.

3.1. Cultural Semantic Extraction Stage

Effective modeling of cultural semantics is a prerequisite for the digital representation of cultural imagery and generative design. In design practice and cultural communication studies, researchers have proposed various semantic extraction approaches aimed at identifying representative conceptual units and structural relationships from heterogeneous cultural information. Common methods include literature quotation analysis, image semantic annotation (Zhang et al., 2012), qualitative interviews, and questionnaire surveys. These methods each have specific advantages in terms of data sources, semantic granularity, and applicable contexts (see Table 1). Therefore, in cultural creative design tasks, researchers can flexibly select or integrate these methods according to specific design objectives and semantic depth requirements to establish a representative cultural semantic framework that supports subsequent clustering modeling and visual generation.

Table 1. Common Methods for Cultural Semantic Extraction.

Method	Data Source	Advantages	Limitations
Literature Quotation Analysis	Online texts, historical documents, academic literature	Semantically rigorous; structurally coherent	Depends on the quality of literature and language processing capabilities
Image Semantic Annotation	Museum images, artifact photos, visual materials	Highly visual; suitable for visual modeling	Limited in capturing abstract concepts; reliant on manual annotation accuracy
Qualitative Interview	Domain experts, intangible cultural heritage bearers	Deep semantic interpretation; capable of extracting tacit knowledge and cultural context	Subjective; limited sample size
Questionnaire Survey	General public, online corpora	Reflects contemporary user perceptions and cultural associations	High noise; limited cultural depth

3.2. Semantic Extraction and Co-occurrence Network Construction Stage

Following the initial extraction of cultural semantic vocabulary, this stage proceeds with semantic categorization and structural modeling to identify frequently occurring cultural elements within the collected materials and uncover their underlying semantic relationships. By segmenting cultural texts into individual sentences and applying part-of-speech tagging, high-frequency noun terms are extracted. A frequency distribution map is then constructed to reveal the dominant features of the main cultural themes.

A keyword co-occurrence analysis method is introduced here. Based on a sliding window mechanism, it calculates the co-occurrence relationships between high-frequency terms to construct a co-occurrence network graph. This method traverses the noun sequences and, within a predefined window size k, counts the co-occurrence frequency of word pairs (w_i, w_j) using the following formula, see Equation (1):

$$\text{CoOccur}(w_i, w_j) = \textstyle\sum_s \in D \sum\_\{i < j, |i - j| < k\}\ \delta(w_i, w_j \mid s) \tag{1}$$

Where: D represents the set of all sentences in the corpus. w_i and w_j are noun keywords appearing within the same sentence. k is the sliding window size (set to 5 in this study). δ (w_i, w_j | s) is an indicator function: it equals 1 if the word pair co-occurs within the window in sentence s, and 0 otherwise.

3.3. Semantic Mapping Stage

The semantic mapping stage aims to transform abstract cultural semantic structures into concrete elements that can be used in texture design generation. To enhance the historical depth and contextual adaptability of the semantic mapping, this study adopts the "event node" modeling paradigm from the CIDOC CRM framework (Dörr, 2002). During the construction of the semantic–design mapping relationships, various cultural semantics are annotated with related historical backgrounds, regional characteristics, and cultural dissemination paths. These contextual associations serve as references for expert scoring and weight assignment, improving both the cultural accuracy and structural integrity of the semantic mapping process.

3.4. Generative Design Stage

The generative design stage aims to translate the previously established semantic–design mappings into concrete automotive interior texture patterns, enabling cross-modal expression from cultural semantics to visual language. At this stage, the semantic–design mapping matrix serves as the input parameter for image generation models and design platforms to automatically generate texture solutions aligned with cultural imagery. Current mainstream generative technologies include diffusion model-based tools and systems based on GANs (see Table 2). To ensure the usability and cultural consistency of the generated outcomes, this stage incorporates expert evaluation mechanisms or user feedback loops. These iterative assessments help refine and optimize the preliminary outputs, progressively leading to high-quality design solutions.

Table 2. Comparison of Tools for Cultural Semantics-Driven Texture Generation.

Category	Diffusion Model Tools	GAN Systems	Cross-Modal Generation Platforms
Platform/ Algorithm	Stable Diffusion / ControlNet / ComfyUI	StyleGAN / DCGAN	Midjourney / RunwayML
Generation Mechanism	Diffusion models with CLIP-based text-image alignment	Adversarial learning with generator-discriminator optimization	Multimodal pre-trained models integrating LLMs with image generation modules
Cultural Adaptation Method	Text and image prompts; controllable style and structure	Style transfer based on sample images; suitable for transforming traditional patterns	Input via keywords, tags, or descriptive text; supports contextual and associative generation
Typical Use Cases	High-precision cultural texture design,	Generating new textures from traditional patterns	Rapid concept visualization and iterative inspiration exploration for cultural imagery

4. Case Study

In recent years, as consumer markets have increasingly emphasized personalization and cultural value, many automotive brands have begun to explore culturally-driven design strategies to enhance brand identity and emotional resonance. Among them, the automotive brand BYD has actively integrated traditional Chinese cultural elements into its product line, launching vehicle series such as “Han,” “Tang,” and “Qin,” which are rich in symbolic cultural significance. These efforts not only reflect cultural confidence but also create distinct brand recognition in product design.

To validate the feasibility and operability of the proposed cultural semantic modeling and generative design methodology, this case study focuses on Han culture as the entry point and explores decorative texture design within the automotive interior system. Through the construction of a semantic resource base, extraction of cultural imagery, mapping to design dimensions, and texture generation, this section demonstrates the practical applicability and scalability of the proposed approach in real-world design contexts.

4.1. Sample Selection

To ensure the depth of cultural information extraction and the traceability of semantic analysis, this study adopts literature quotation analysis as the primary data collection method. Using the keyword “Han cultural elements,” a targeted search was conducted on www.cnki.net to retrieve and screen high-quality Chinese-language literature from recent years. A total of 28 representative academic documents highly relevant to the research topic were selected as data sources for cultural semantic extraction, including 22 research papers and 6 master’s theses. The literature spans multiple disciplines such as design studies, art studies, archaeology, linguistics and literature, and management, covering the period from 2015 to 2025, with a total word count of approximately three hundred and ten thousand Chinese characters.

In parallel with text collection, a supplementary process of visual sample gathering and curation was conducted to enhance the operability of the texture generation stage and support intuitive evaluation. This included collecting representative images, pattern references, and cultural symbol examples cited in the literature. A total of 48 image samples were gathered. This step supports more targeted semantic-to-visual mapping, provides visual references for expert evaluation and user feedback, and improves both the accuracy and interpretability of the assessment process.

4.2. Cultural Imagery Extraction

Following text cleaning and preprocessing, this section focuses on the extraction of cultural imagery terms. Based on a frequency analysis of the top 800 terms, high-frequency words from the selected “Han cultural elements” literature were manually screened. It was first noted that some terms, such as “Xuzhou City (420)” and “Xi’an City (231),” primarily denote specific geographical locations. While culturally relevant, these terms lack direct design implications in the context of automotive interior design and were therefore excluded. Similarly, general-purpose terms such as “aspect (189)” and “period (186),” which lack clear semantic directionality, were also removed.

Moreover, certain culturally significant terms like “ruin (326)” and “Han tomb (294)” were excluded due to their potential to introduce aesthetic discord or cultural inappropriateness in interior design applications. As a result, after combining frequency-based analysis with manual semantic filtering, a total of 20 representative Han cultural imagery terms were preliminarily extracted (see Table 3).

Table 3. Preliminary Selection of High-Frequency Han Cultural Imagery Terms.

Cultural Imagery Term (Frequency)			
Lacquerware (194)	Dragon Pattern (33)	Dragon and Phoenix Motif (14)	Black Lacquer (11)
Pictorial Stone Relief (170)	Phoenix Pattern (21)	Chariot and Horse (13)	Azure Dragon (10)
Cloud Pattern (41)	Golden Color (18)	Phoenix (12)	Vermilion Bird (10)
Silk Weaving (37)	Scroll Clouds (18)	Jade Artifact (12)	Bronze Mirror (10)
Central Axis (35)	Yellow Colour (14)	Silk Fabric (11)	Paper Cutting (10)

4.3. Semantic Mapping

To ensure that the semantic elements used in the subsequent design generation phase possess both cultural accuracy and design applicability, this study introduced an expert evaluation mechanism for systematic refinement. Specifically, an expert panel was formed consisting of three cultural scholars and three automotive interior designers, aiming to integrate both academic and industry perspectives for a more comprehensive identification and analysis of relevant terms.

The expert panel evaluated each cultural imagery term across three dimensions: cultural representativeness, visual translatability, and user emotional acceptance, using a 5-point Likert scale. Based on average scores, six highly adaptive terms were selected as core objects for subsequent semantic modeling. Ultimately, through a combination of frequency analysis and expert evaluation, six high-frequency Han cultural terms—jade artifact, cloud pattern, vermilion bird, golden color, silk fabric, and phoenix pattern—were identified as the primary semantic inputs for texture design generation (see Table 4).

Table 4. Evaluation Results of High-Frequency Han Cultural Imagery Terms.

Cultural Imagery Term	Cultural Representativeness	Visual Translatability	User Emotional Acceptance	Average Score
Jade Artifact	3.83	4.33	4.33	4.16
Cloud Pattern	3.83	4.67	4.33	4.28
Vermilion Bird	4.33	4.33	4.33	4.33
Golden Color	4.00	4.50	4.67	4.39
Silk Fabric	4.17	4.67	4.33	4.39
Phoenix Pattern	4.83	4.50	4.33	4.55

Building on this foundation, a structured set of semantic knowledge triples was constructed with reference to the "Entity–Event–Context" modeling paradigm from the CIDOC CRM framework. Specifically, the selected cultural imagery terms were defined as semantic entities (Entity). These were annotated with corresponding historical and cultural contexts and societal functions (Event)—such as ritual systems, decorative traditions, and mythological narratives—based on literature review and iconographic analysis. Further, the design-related context (Context) was extracted, identifying each term's translational value and visual expression characteristics in modern automotive interior design. This process yielded semantic units that can be used for prompt control and image generation.

For instance, jade artifact symbolizes status and ritual, and is suitable for constructing textures with geometric regularity and symmetrical layering. Cloud pattern, originating from Han Dynasty royal decorations, expresses fluidity and rhythm, often appearing in borders or background motifs. Vermilion bird and phoenix pattern, derived from mythological creatures and symbolic ornaments, are ideal for generating mysterious, symmetrical, and highly recognizable compositions. Meanwhile, golden color and silk fabric contribute to the texture generation through their semantic associations with color and material, conveying luxury, softness, and aesthetics rooted in Eastern cultural imagery.

Through this semantic hierarchy and relational modeling process, a structured cultural foundation was established to support subsequent texture generation and semantic mapping. Finally, considering the aesthetic and functional characteristics of automotive interior design, a curated list of cultural imagery terms was identified—via manual evaluation and semantic filtering—as core inputs for clustering and generative stages in this study (see Table 5).

Table 5. Structured Semantic Knowledge Triples for Han Culture.

Cultural Imagery Term (Entity)	Historical Context / Cultural Scenario (Event)	Design Semantics / Contextual Expression (Context)
Jade Artifact	Ritual system, symbol of social status	Geometric regularity, clear hierarchical layering, symbolizing nobility
Cloud Pattern	Royal iconography, ritualistic and decorative elements	Flowing curves, strong rhythm, used in borders or background embellishments
Vermilion Bird	Eastern mythical creature, astronomical beliefs	Symmetrical composition, guardian symbolism, conveys mystery and dignity
Golden Color	Imperial symbolism, ceremonial clothing	High gloss, sense of luxury, emphasizes centrality and ceremonial atmosphere
Silk Fabric	Royal textiles, emblem of identity	Soft texture, intricate patterns, embodies traditional Eastern aesthetics
Phoenix Pattern	Mythological themes, auspicious symbolism	Complex structure, evokes a sense of dynamic flight

4.4. Design Generation Implementation

In the design generation phase, this study constructed semantic prompt templates based on the selected cultural imagery terms and their corresponding semantic clusters. Specifically, the prompt formulation incorporated multiple semantic dimensions, including cultural motifs (e.g., phoenix pattern, cloud pattern) and material properties (e.g., silk fabric, golden color). This enabled the generative system to effectively express cultural connotations across aspects such as style, composition, and detail articulation. By inputting the constructed prompts into Midjourney, the system enables the generation of culturally inspired texture patterns.

Specifically, we employed Midjourney's sixth-generation diffusion model (v6) with selected reference style images. Key parameters include --style raw (to retain original stylistic fidelity), --tile (to enable seamless pattern tiling), and --ar 16:9 (to fit the horizontal layout of automotive interior surfaces). The tile parameter ensures that the generated textures are seamlessly repeatable, while aspect ratio defines the compositional structure, and style raw enhances the semantic fidelity between prompt input and visual output.

Through a prompt construction mechanism driven by semantic inputs, the model achieves effective cultural control over the generated content. In this process, semantic labels function as a form of "soft guidance," serving to constrain the visual theme and stylistic attributes during image generation. This process achieved an automated translation from abstract cultural semantic units to concrete visual texture compositions (see Figure 2a). The resulting images demonstrate wide applicability in the decorative texture design of automotive components such as steering wheels, center consoles, and instrument panels.

Following the initial generation, a multi-round manual evaluation and aesthetic selection was conducted on the AIGC-generated outputs. The assessment covered dimensions including artistic value, cultural appropriateness, visual appeal, manufacturability, and user acceptance. Representative design samples were shortlisted (see Figure 2b), and after manual refinement, rendering simulations were produced to demonstrate the application of these textures in actual automotive interior contexts (see Figure 2c).

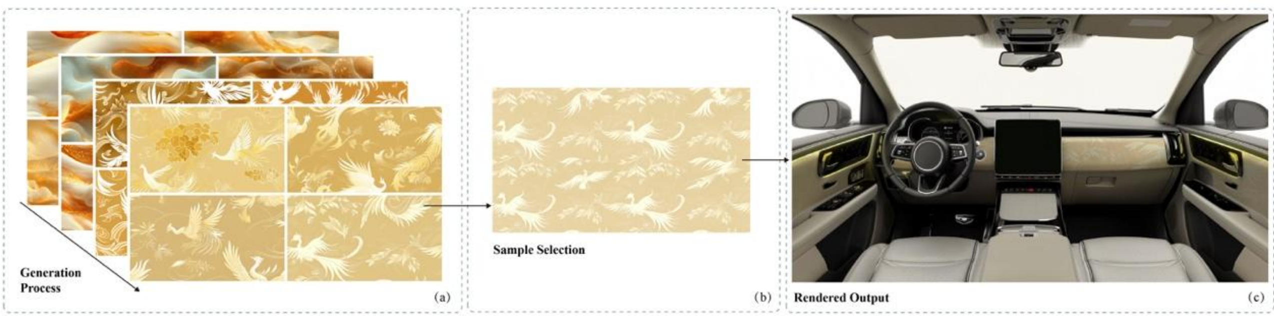

Figure 2. Generation Workflow and Final Outputs: (a) Generation Process; (b) Sample Selection; (c) Rendered Output.

5. Results

To validate the feasibility and user acceptance of the proposed cultural semantic modeling and generative design method for automotive interior textures, this study conducted a satisfaction analysis using the Fuzzy Comprehensive Evaluation Method (Wu & Hu, 2020). Based on fuzzy set theory, an evaluation index set was established, where the automotive interior design solution is viewed as a fuzzy set U composed of multiple factors. The first-level evaluation indices include visual aesthetics, cultural consistency, innovativeness, user preference, and practical feasibility, forming the set: $U = \{U_1, U_2, U_3, U_4, U_5\}$. Next, an evaluation grade set was defined. In this study, the levels include “Very Satisfied (100 points),” “Satisfied (75 points),” “Neutral (50 points),” and “Dissatisfied (25 points)”, forming the set: $V = \{V_1, V_2, V_3, V_4\}$.

Upon collecting the sample evaluation data, a fuzzy evaluation matrix R was constructed according to the degree of membership of each criterion across the defined evaluation grades. The general form of the matrix is shown in Equation (2):

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{21} & r_{22} & r_{23} & r_{24} \\ r_{31} & r_{32} & r_{33} & r_{34} \\ r_{41} & r_{42} & r_{43} & r_{44} \\ r_{51} & r_{52} & r_{53} & r_{54} \end{bmatrix} \tag{2}$$

where r_{if} represents the membership degree of the *i* evaluation criterion corresponding to the *j* evaluation level.

A weight vector W was then defined to represent the importance of each evaluation criterion. In this study, equal weights were assigned to all five criteria: W = (0.2, 0.2, 0.2, 0.2, 0.2). Finally, the overall satisfaction score was calculated using the fuzzy comprehensive evaluation formula, as shown in Equation (3):

$$R_f = W \times R \tag{3}$$

A total of 13 participants—including 3 experts and 10 potential users—evaluated the design samples. The resulting membership degrees for each satisfaction level were: Very Satisfied: 0.185, Satisfied: 0.585, Neutral: 0.231, and Dissatisfied: 0.000. The final comprehensive satisfaction score was 73.85 out of 100, indicating a generally high level of agreement and recognition among participants regarding the visual quality, cultural alignment, and user relevance of the design solutions.

In summary, the proposed method successfully achieved an effective mapping from cultural semantics to texture pattern generation and received positive evaluations from both experts and users during its practical implementation. This suggests that the culture-driven generative design approach has strong feasibility and potential for application in automotive interiors.

6. Conclusion

This study presents a systematic investigation into an automotive interior texture design method based on cultural semantic modeling and generative design. A complete design framework covering cultural imagery extraction, semantic structure construction and visual generation is proposed. The study first conducts cultural semantic extraction, builds a cultural vocabulary list, and identifies representative cultural imagery through frequency analysis and co-occurrence network construction. Secondly, the semantic elements are structurally encoded into the input cue vectors of the generative design using the “Entity–Event–Context” modeling paradigm of CIDOC CRM. Finally, in the generation phase, a series of culturally inspired texture designs are generated using a diffusion-based image generation platform, and the visual effect and user satisfaction are evaluated using a fuzzy comprehensive evaluation method.

The case study on Han cultural semantics demonstrated that the proposed method effectively uncovers deep-level cultural information and translates it into controllable visual texture elements. The method significantly enhances the cultural expressiveness and emotional recognizability of automotive interiors. This research not only provides a structured and scalable semantic modeling pathway for cultural and creative product design but also offers theoretical and methodological support for personalized in-vehicle design in the AIGC era.

Despite its methodological contributions and practical outcomes, the study also presents certain limitations. The semantic modeling relied mainly on literature quotation analysis, and the sample size may be limited. Since most texts were sourced from academic publications, the extracted vocabulary tends to be abstract and theoretical, which may reduce the practical translatability of some terms in design contexts. In addition, the selection of literature affects the clustering and co-occurrence results—topic deviation or inconsistent styles in the corpus may weaken semantic accuracy. Despite efforts to expand keyword coverage, some terms still present contextual ambiguity or low design relevance.

To address these issues, future research could incorporate diverse data sources—such as social media comments, exhibition feedback, and annotated image datasets—and apply multimodal semantic analysis techniques to improve the precision of cultural element identification and the contextual adaptability of the design output. Furthermore, introducing additional parameter control mechanisms in the generative stage is recommended to enhance the mapping accuracy between semantics and texture features, thereby improving the controllability and cultural distinctiveness of the generated results.

List of Abbreviations

CIDOC CRM	CIDOC Conceptual Reference Model
AIGC	Artificial Intelligence Generated Content
GAN	Generative Adversarial Network

Data Availability Statement

Data generated during this study are included in this published article.

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Conflicts of Interest

The authors declare no competing interests.

Author's Contributions

Conceptualization, S.X.Z. and S.Y.Z.; methodology, S.X.Z.; software, S.Y.Z.; validation, S.X.Z.; resources, S.X.Z. and S.Y.Z.; data curation, S.X.Z.; writing—original draft preparation, S.X.Z. and S.Y.Z.; writing—review and editing, S.X.Z.; visualization, S.X.Z. and S.Y.Z. All authors have read and agreed to the published version of the manuscript.

References

Bruseker, G., Carboni, N., & Guillem, A. (2017). Cultural Heritage Data Management: The Role of Formal Ontology and CIDOC CRM. In M. L. Vincent, V. M. López-Menchero Bendicho, M. Ioannides, & T. E. Levy (Eds.), *Heritage and archaeology in the digital age: acquisition, curation, and dissemination of spatial cultural heritage data* (pp. 93-131). Springer International Publishing. https://doi.org/10.1007/978-3-319-65370-9_6

Chu, S. (2003). Cross-cultural comparison of the perception of symbols. *Journal of Visual Literacy*, *23*(1), 69-80. https://doi.org/10.1080/23796529.2003.11674592

Dörr, M. (2002). The cidoc crm-an ontological approach to semantic interoperability of metadata, 2001. *AI Magazine, Special Issue on Ontologies*.

Faruqi, F., Perroni-Scharf, M., Walia, J. S., Zhu, Y., Feng, S., Degraen, D., & Mueller, S. (2025). TactStyle: Generating Tactile Textures with Generative AI for Digital Fabrication. Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems.

Hofstede, G. (1991). Cultures and organizations: Software of the mind. *McGraw Hills*.

Inbasekaran, A., Gnanasekaran, R. K., & Marciano, R. (2021). Using Transfer Learning to contextually Optimize Optical Character Recognition (OCR) output and perform new Feature Extraction on a digitized cultural and historical dataset. 2021 IEEE International Conference on Big Data (Big Data).

Knight, E., Gunawardena, C. N., & Aydin, C. H. (2009). Cultural interpretations of the visual meaning of icons and images used in North American web design. *Educational Media International*, *46*(1), 17-35. https://doi.org/10.1080/09523980902781279

Liang, X. (2022). Traditional Pattern Feature Extraction and Cultural Creative Design Application Based on Multilevel Histogram

Shape Segmentation. *Mobile Information Systems*, *2022*(1), 3581570. https://doi.org/10.1155/2022/3581570

Lin, C.-H., Gao, J., Tang, L., Takikawa, T., Zeng, X., Huang, X., Kreis, K., Fidler, S., Liu, M.-Y., & Lin, T.-Y. (2023). Magic3d: High-resolution text-to-3d content creation. Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.

Ma, K., & Chung, J. (2023). A Research on 3D Texture Production Using Artificial Intelligence Softwear. *International Journal of Internet, Broadcasting and Communication*, *15*(4), 178-184. https://doi.org/10.7236/IJIBC.2023.15.4.178

Michel, O., Bar-On, R., Liu, R., Benaim, S., & Hanocka, R. (2022). Text2mesh: Text-driven neural stylization for meshes. Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.

Moraitou, E., Christodoulou, Y., & Caridakis, G. (2022). Semantic models and services for conservation and restoration of cultural heritage: A comprehensive survey. *Semantic Web*, *14*(2), 261-291. https://doi.org/10.3233/SW-223105

Shimomura, M., Oba, G., Sakae, Y., Kokado, N., Kato, T., & Matsuoka, Y. (2024). Ai-based texture design system based on age thinking model. *Journal of the Science of Design*, *8*(1), 1_31-31_40. https://doi.org/10.11247/jsd.8.1_1_31

Su, C., Peng, Y., Huang, S., & Chen, Y. (2020). A Metaphor Comprehension Method Based on Culture-Related Hierarchical Semantic Model. *Neural Processing Letters*, *51*(3), 2807-2826. https://doi.org/10.1007/s11063-020-10227-6

Wu, L., Cao, D., Yang, J., Zhang, R., & Yan, X. (2024). The Symbolization of Regional Elements Based on Local-Chronicle Text Mining and Image-Feature Extraction. *ISPRS International Journal of Geo-Information*, *13*(9), 299.

Wu, X., & Hu, F. (2020). Analysis of ecological carrying capacity using a fuzzy comprehensive evaluation method. *Ecological Indicators*, *113*, 106243. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.106243

Xian, W., Sangkloy, P., Agrawal, V., Raj, A., Lu, J., Fang, C., Yu, F., & Hays, J. (2018). Texturegan: Controlling deep image synthesis with texture patches. Proceedings of the IEEE conference on computer vision and pattern recognition.

Yin, J., & Song, B. (2024). Innovative 3D Character Model Texture Mapping Solution Based on Artificial Intelligence Image Generation Model. *International Journal of Contents*, *20*(4), 14-21. https://doi.org/10.5392/IJoC.2020.20.4.014

Yoo, W. S., Kim, J. G., Kang, K., & Yoo, Y. (2021). Extraction of colour information from digital images towards cultural heritage characterisation applications. *SPAFA Journal*, *5*, 1-14. https://doi.org/10.26721/spafajournal.2021.v5.690

Yuan, B., Wu, K., Wu, X., & Yang, C. (2024). Form generative approach for front face design of electric vehicle under female aesthetic preferences. *Advanced Engineering Informatics*, *62*, 102571. https://doi.org/https://doi.org/10.1016/j.aei.2024.102571

Zhang, D., Islam, M. M., & Lu, G. (2012). A review on automatic image annotation techniques. *Pattern Recognition*, *45*(1), 346-362. https://doi.org/https://doi.org/10.1016/j.patcog.2011.05.013

Zhu, Y., Faruqi, F., & Mueller, S. (2024). Generative AI in Color-Changing Systems: Re-Programmable 3D Object Textures with Material and Design Constraints. *arXiv preprint arXiv:2404.17028*. https://doi.org/10.48550/arXiv.2404.17028