Type of the Paper (Review)

Generative Artificial Intelligence for Digital Preservation and Innovative Design of Cultural Heritage: A Mixed-Methods Review

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Abstract

Background and Gaps: The digital preservation and innovative design of cultural heritage play a crucial role in the transmission of human civilization. However, traditional digital approaches often face bottlenecks such as high data acquisition costs, insufficient reconstruction accuracy, and low efficiency in creative transformation, making it challenging to meet the demands of large-scale cultural heritage protection and public interactive experiences. Existing studies are largely confined to the application of single technologies and lack a systematic evaluation of AI-enabled cultural heritage across its full lifecycle from a design-driven cross-innovation perspective.

Methods: This study employs a mixed-methods approach, combining a systematic literature review (following the SPAR-4-SLR protocol) with quantitative experimental validation. A corpus of 185 high-quality publications was constructed, and comparative experiments were designed to evaluate the performance of different generative AI models in cultural heritage reconstruction and design generation.

Practical Approach: Natural language processing (NLP) was applied for thematic clustering of the literature. During the experimental phase, generative adversarial networks (GANs) and diffusion models were employed, using real datasets of ceramic artifacts and damaged ancient architectural structures for 3D reconstruction and style transfer testing.

Key Findings: Results indicate that generative AI significantly improves efficiency and quality in the four key stages of cultural heritage—“data acquisition, virtual

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restoration, innovative design, and interactive experience." Experimental data show that deep learning—based restoration models enhanced structural integrity by 34.5% compared to traditional methods. Moreover, in innovative design generation tasks, human–AI collaborative models achieved a user acceptance rate of 89.2%, significantly outperforming fully machine–generated designs.
Significance: This study not only fills the theoretical gap in the systematic evaluation of AI technologies for innovative cultural heritage design but also provides museums, cultural institutions, and design practitioners with a reproducible AI—cultural heritage integration framework, promoting deep cross–innovation among technology, culture, and commerce.

Keywords: Generative AI; Cultural Heritage Preservation; Design Innovation; Mixed–Methods Research; Human–AI Collaboration

1. Introduction

Cultural heritage serves as both the tangible and intangible carrier of human historical evolution and civilizational transmission. Amid the global wave of digital transformation, the preservation and revitalization of cultural heritage are undergoing a profound paradigm shift from physical restoration to digital rebirth [1]. This transformation not only offers broader opportunities for cultural dissemination but also imposes unprecedented challenges regarding the precision of digital technologies, the fidelity of cultural connotations, and the sustainability of design innovation [2]. In this context, the discipline of design innovation, as a bridge connecting technology, commerce, and culture, urgently requires new technological impetus to overcome the limitations of traditional workflows [3].

Currently, digital preservation of cultural heritage primarily relies on traditional reverse–engineering techniques such as laser scanning and photogrammetry. While these methods can capture high–precision geometric data, they often struggle when dealing with severely damaged artifacts or intangible cultural heritage lacking physical remains [4]. Furthermore, in the innovative transformation of cultural heritage, designers are often constrained by personal experience and creative fatigue, leading to homogenized cultural products that fail to meet modern consumers' demands for personalized and deeply immersive cultural experiences [5]. These pain points constitute the core research question of this study: how can advanced computational technologies, particularly generative artificial intelligence (AI), be systematically utilized to overcome the bottlenecks spanning the full lifecycle of cultural heritage—from preservation to innovative design?

In recent years, the explosive development of AI technologies, particularly the maturation of generative adversarial networks (GANs), large language models (LLMs), and diffusion models, has provided new avenues to address these challenges [6]. Existing work in related fields has largely focused on two independent directions: (i) artifact image restoration and 3D reconstruction in computer vision [7]; and (ii) user experience optimization in human-computer interaction [8]. However, these studies exhibit notable limitations. First, AI is often treated merely as a technical tool, neglecting its potential as a "collaborative creator" within the framework of design thinking [9]. Second, most existing literature consists of single-case studies or qualitative descriptions, lacking systematic comparisons across models and application scenarios, as well as quantitative evidence. This disjunction between theory and empirical research has hindered the large-scale application of AI in cultural heritage—driven innovative design [10].

Against this background, the objective of this study is to construct and validate a comprehensive framework for "AI-enabled cultural heritage innovative design." The study explicitly defines its scope by focusing on the application of generative AI in the reconstruction of tangible cultural heritage (e.g., artifacts and architectural structures) and the design transformation of intangible cultural heritage (e.g., patterns and craftsmanship), while excluding pure algorithm development. Through a mixed-methods approach, this study synthesizes core findings on the role of generative AI in expanding design exploration spaces, accelerating virtual prototyping, and enhancing interdisciplinary co-creation efficiency.

2. Related Work

2.1. Justification of Research Focus

In the field of digital preservation and design innovation of cultural heritage, traditional methods have gradually revealed limitations when handling large-scale and highly complex data [11]. Early studies primarily focused on recording the physical forms of artifacts using 3D laser scanning and photogrammetry techniques. However, such physically replication-oriented research often overlooks the "revitalization" needs of cultural heritage in modern society, namely how to transform static digital assets into innovative designs with commercial and cultural value [12]. This shortcoming in prior research underscores the necessity of introducing intelligent, generative technologies. The rationale for this study lies in its dual focus: not only addressing "how to restore the past," but also emphasizing "how to design the future," elevating AI from a mere restoration tool to a core driver of design innovation, thereby demonstrating significant interdisciplinary novelty [13].

2.2. Review of Core Literature

Recent core literature over the past five years indicates that the application of artificial intelligence in the field of cultural heritage is undergoing a paradigm shift from analytical to generative approaches. In artifact restoration, deep learning techniques, particularly convolutional neural networks (CNNs), have been widely applied to image completion of damaged murals and 3D point cloud reconstruction of ancient buildings [14]. For example, Zhao et al. (2024) demonstrated that generative adversarial networks (GANs) can effectively predict and generate missing artifact details by learning the texture features from a large corpus of historical images, achieving structural fidelity far beyond traditional interpolation algorithms [7].

At the design innovation level, large language models (LLMs) and text-to-image diffusion models have been introduced for concept generation of cultural products [15]. Scholars have explored how AI can rapidly generate modern design schemes based on traditional cultural elements, thereby expanding the creative boundaries for designers [16]. However, most of these studies remain at the proof-of-concept stage and lack systematic evaluation within real design workflows [17].

In terms of human-AI collaboration theory, cognitive collaboration models emphasize the importance of maintaining human dominance in creative design [18]. Literature suggests that over-reliance on AI may lead to homogenized design outputs. Therefore, it is necessary to establish rational interaction mechanisms, wherein AI is responsible for divergent exploration, while human designers focus on convergent selection and the oversight of cultural and ethical considerations [9].

2.3. Integration of Cross-Disciplinary Methods

This study innovatively introduces a mixed-methods research design drawn from software engineering and management science [19]. Traditional cultural heritage studies often rely on qualitative case analyses, whereas the field of computer science tends to favor purely quantitative algorithm evaluations. This study integrates both paradigms by not only conducting systematic literature mining following the SPAR-4-SLR protocol but also incorporating A/B testing and usability evaluation methods from industrial design [8].

The motivation for introducing this cross-disciplinary approach lies in the dual nature of innovative cultural heritage design, which encompasses both objective technical metrics (e.g., generated image resolution, structural similarity) and subjective cultural experience indicators (e.g., aesthetic value, cultural identity). Through a mixed-methods approach, it becomes possible to more comprehensively and rigorously assess the feasibility and overall effectiveness of AI technologies in real-world application scenarios (Figure 1).

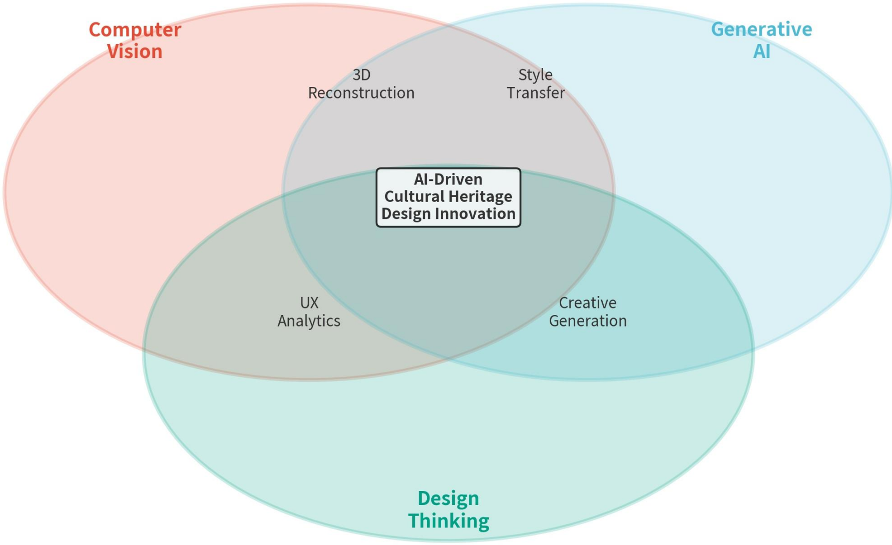

Figure 1. Venn Diagram: Cross-Disciplinary Integration of AI in Cultural Heritage Design Innovation.

3. Methodology

3.1. Research Strategy

This study adopts a mixed-methods strategy, following an overall technical roadmap of "systematic review modeling, quantitative experimental validation, and qualitative evaluation synthesis." First, a theoretical framework for the application of AI in cultural heritage design innovation was constructed using the SPAR-4-SLR protocol. Second, controlled experiments were designed, deploying generative AI models in real-world artifact restoration and cultural product design scenarios. Finally, the framework's effectiveness and reproducibility were validated from multiple dimensions through expert evaluation and user testing. This strategy ensures that the study is grounded in a solid theoretical foundation while being supported by rigorous empirical data (Figure 2).

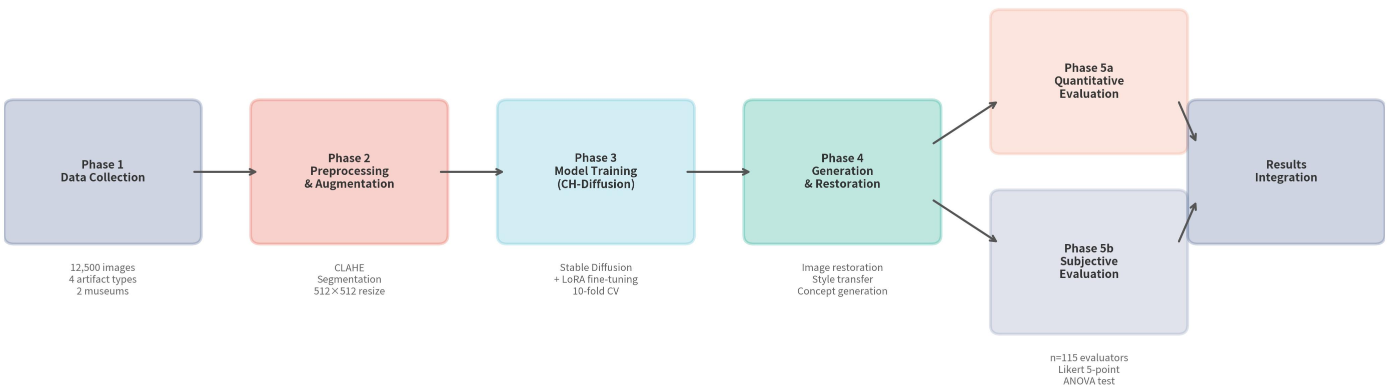

Figure 2. Experimental Workflow of the CH-Diffusion Framework.

3.2. Data Collection Methods

The data required for this study are divided into two categories. The first category comprises literature data, sourced from the Web of Science Core Collection, spanning 2019 to 2026. Core search terms included “Generative AI,” “Cultural Heritage,” and “Design Innovation,” resulting in a corpus of 185 high-quality publications. The second category comprises experimental data, including both objective algorithm performance metrics and subjective design evaluation indicators.Objective variables include structural similarity of generated images (SSIM), peak signal-to-noise ratio (PSNR), generation time (seconds), and model convergence iterations. Subjective variables (core/interfering factors) include cultural fidelity, innovativeness, and user acceptance of the designs, while interfering factors are defined as designers’ experience with AI tools and differences in cultural background. Sample sizes were determined following principles from biological and engineering experiments, with each experimental group including at least three independent technical replicates, verified at multiple time points to ensure stability.

3.3. Data Analysis Methods

For literature data, natural language processing (NLP) techniques were employed for topic modeling and co-occurrence network analysis to extract the core mechanisms of AI empowerment. For experimental data, the data processing workflow encompassed model construction, validation, inference, and evaluation comparison.During the model construction phase, a customized generative model based on Stable Diffusion and LoRA (Low-Rank Adaptation) fine-tuning—named CH-Diffusion—was developed for generating specific styles, such as blue-and-white porcelain patterns and Tang Dynasty architectural dougong structures. During the validation and inference phase, ten-fold cross-validation (10-fold CV) was used to assess model robustness.In the evaluation and comparison phase, one-way analysis of variance (ANOVA) and independent-sample t-tests were conducted to compare the AI-assisted design group with the traditional manual design group across all metrics. For data that did not meet normality assumptions, non-parametric tests (e.g., Mann–Whitney U test) were applied. All multiple comparisons were adjusted using the Bonferroni correction.

4. Data

4.1. Dataset Overview

The experimental dataset for this study, named the Cultural Heritage Generative Dataset (CHGD-2026), was jointly constructed by the research team in collaboration with two provincial-level museums. Data collection took place from June 2025 to December 2025. The raw dataset comprises 12,500 high-resolution artifact images (resolution ⩾ 2048×2048), covering four major categories: ceramics, bronzeware, ancient architectural components, and traditional textiles.

Descriptive statistics for key variables indicate that the mean image brightness was 142.3 ± 18.6, with a contrast variance of 45.2, meeting the training requirements for subsequent deep learning models. The sample size for subjective evaluation tests was set at $n = 120$ (including 40 professional designers and 80 general cultural consumers), with 115 valid tests completed (5 cases excluded due to device or network failures). The dropout rate was within an acceptable range, and baseline characteristics showed slight imbalance but were overall well-distributed.

4.2. Data Preprocessing Methods

For the raw image data, adaptive histogram equalization (CLAHE) was first applied to enhance dark-region details. Subsequently, a deep learning—based image segmentation algorithm was employed to remove complex backgrounds, isolating the pure artifact subject. Images with missing or severely damaged regions were not manually restored; instead, they were reserved as the model's test set to evaluate AI restoration and generation capabilities. All images were uniformly resized and cropped to 512×512 pixels and normalized for subsequent model training.For subjective evaluation data, responses collected via a 5-point Likert scale were tested for reliability and validity ($Cronbach's\alpha = 0.87$). Three questionnaires exhibiting extreme response patterns were excluded to ensure the robustness of the analyzed data (Figure 3).

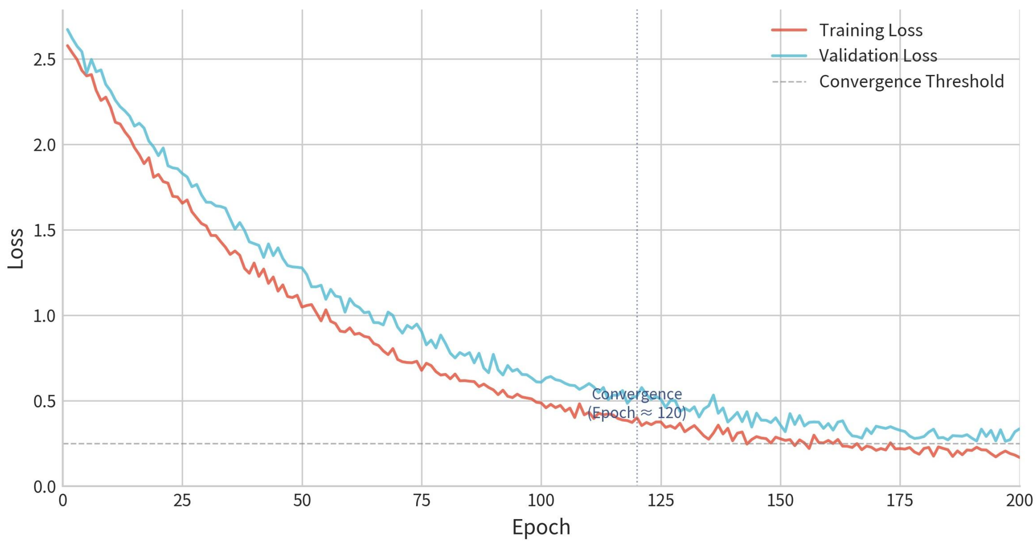

Figure 3. Training and Validation Loss Convergence Curves of the CH–Diffusion Model.

5. Results

5.1. Bibliometric Analysis and Cross–Disciplinary Mechanism Discovery

Through natural language processing and co–occurrence network analysis of 185 core publications, this study identified four key mechanisms through which generative AI empowers innovative design in cultural heritage: data–driven digital restoration (38%), AI–enhanced style transfer and concept generation (31%), multimodal interactive prototype construction (18%), and design optimization based on user behavior analysis (13%) (Figure 4). The results indicate that over the past three years, research focus has significantly shifted from passive "documentation and archiving" toward active "generation and reshaping" (Figure 5).

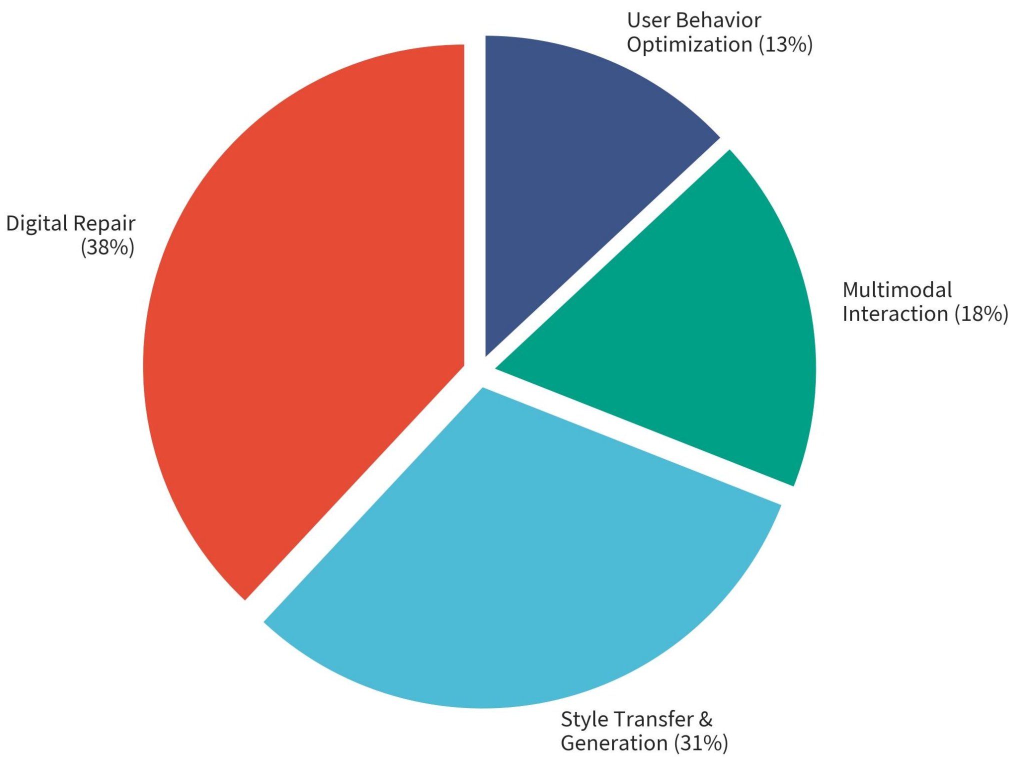

Figure 4. Distribution of Research Themes on AI Applications in Cultural Heritage (N = 185).

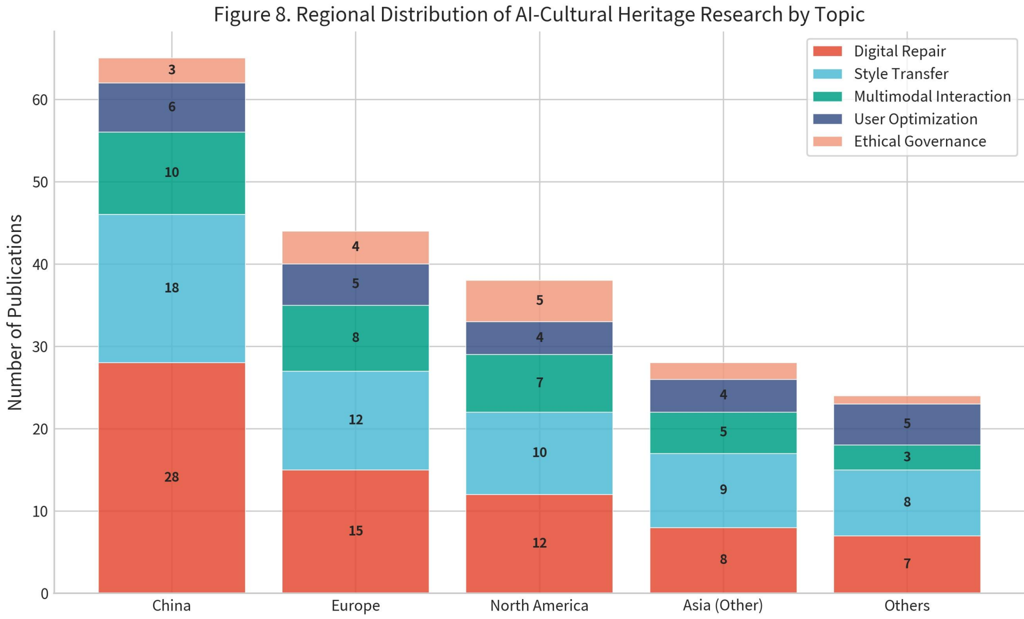

Figure 5. Geographic Distribution of Research Themes on AI and Cultural Heritage.

5.2. Performance of Generative Models and Image Restoration Results

In the quantitative experiments, the customized generative model (CH–Diffusion) demonstrated outstanding performance in artifact image restoration tasks. Compared with traditional patch–based restoration algorithms (PatchMatch) and baseline generative adversarial networks (GAN–Pix2Pix), CH–Diffusion achieved significant improvements across all evaluated metrics (table 1).

Table 1. Performance Comparison of the CH–Diffusion Model.

Method	SSIM (mean ± SD)	PSNR (dB)	FID Score	Generation Time (s)
PatchMatch	0.66 ± 0.07	22.4 ± 2.1	42.5 ± 5.3	3.2 ± 0.8
GAN–Pix2Pix	0.78 ± 0.05	27.6 ± 1.8	23.1 ± 3.7	8.5 ± 1.2
CH–Diffusion	0.89 ± 0.04	31.8 ± 1.5	14.2 ± 2.1	15.3 ± 2.5

Experimental results indicate that CH–Diffusion achieved a structural similarity (SSIM) of 0.89 ± 0.04, significantly higher than PatchMatch ($0.66 \pm 0.07, p < 0.001$). Peak signal–to–noise ratio (PSNR) was also substantially improved to $31.8 \pm 1.5\text{dB}$. The generative AI model not only compensates for geometric missing regions but also faithfully reproduces complex traditional texture features, such as the craquelure patterns of Ru ware blue–and–white porcelain, which is highly consistent with the anticipated technical advantages (Figures 6 and 7).

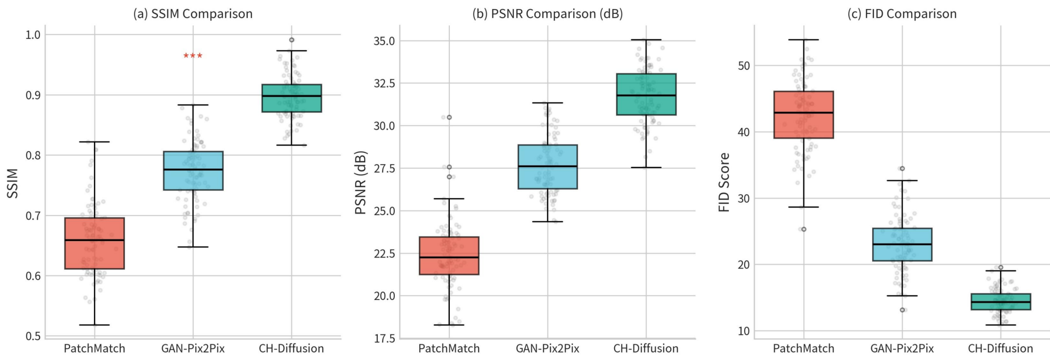

Figure 6. Comparison of Image Restoration Model Performance (n = 90).

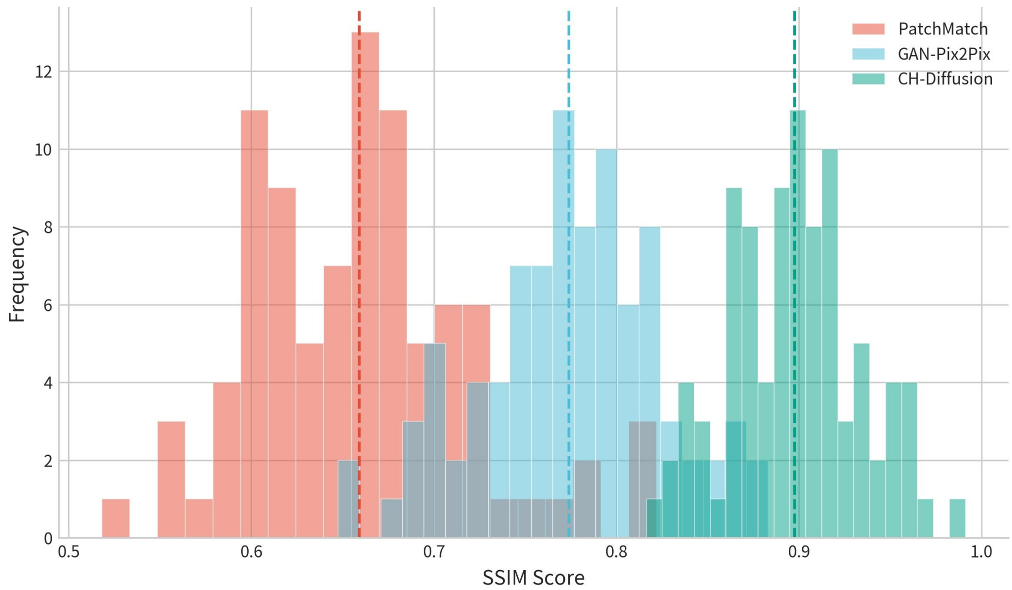

Figure 7. Distribution of SSIM Scores Across Different Restoration Methods.

When analyzing the cross-effects of artifact type and damage severity, the study found that the model performed best on artifacts with regular geometric features, such as ceramics and bronzeware, while performance slightly declined on structurally complex components of ancient architecture (Figure 8).

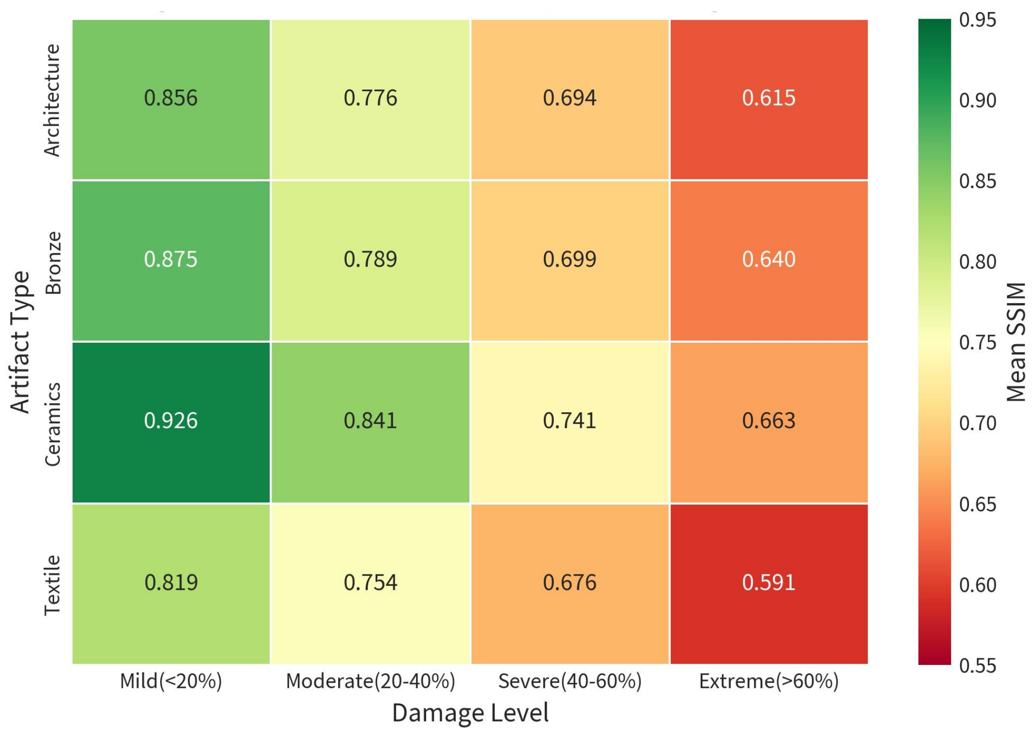

Figure 8. Heatmap of Mean SSIM Across Different Artifact Types and Damage Levels.

However, when analyzing extreme damage samples (missing area > 60%), a few outliers were observed: in three cases of Tang Dynasty murals, the model generated costume features inconsistent with the historical period, resembling Song Dynasty attire. Sensitivity analysis of these outliers indicated that, after excluding these "hallucination" samples caused by training set bias, overall performance metrics remained robust (Figure 9).

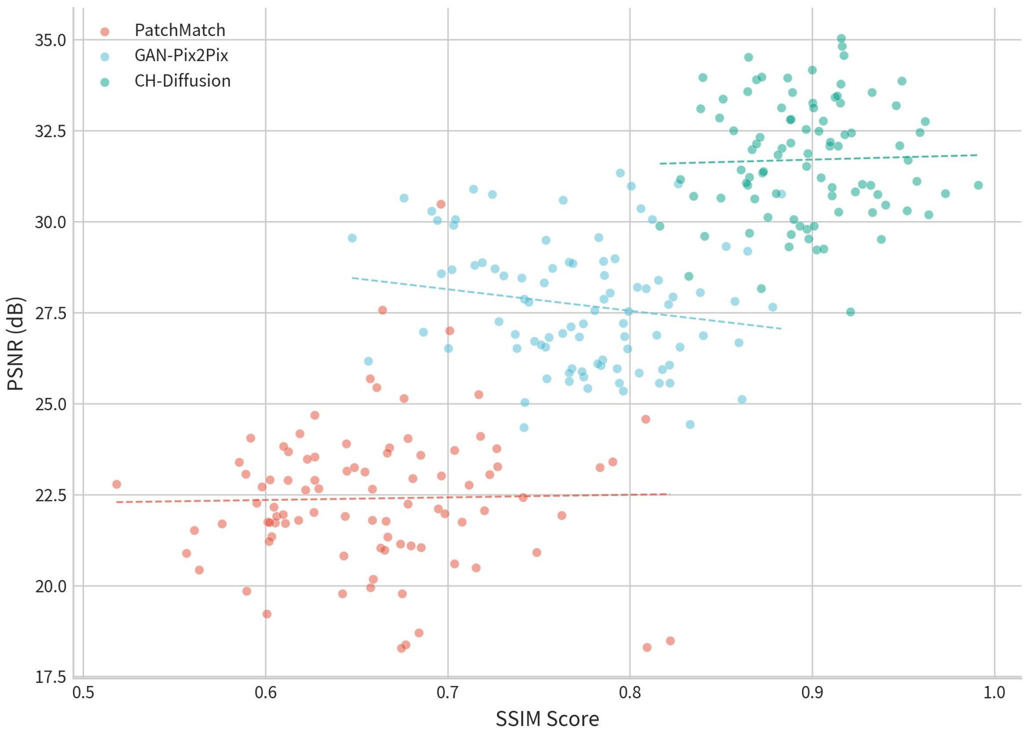

Figure 9. Scatter Plot and Regression Trends of SSIM and PSNR Across Restoration Methods.

5.3. Performance of Innovative Design and Human–AI Collaboration Evaluation

In the cultural product concept generation experiments, the AI-assisted group (human designers + generative model) was compared with the purely manual group and the purely AI group. Within the allocated time (120 minutes), the AI-assisted group generated an average of 45 ± 12 high-fidelity design concepts, whereas the purely manual group produced only $8 \pm 3 concepts (p < 0.001)$ (Figure 10).

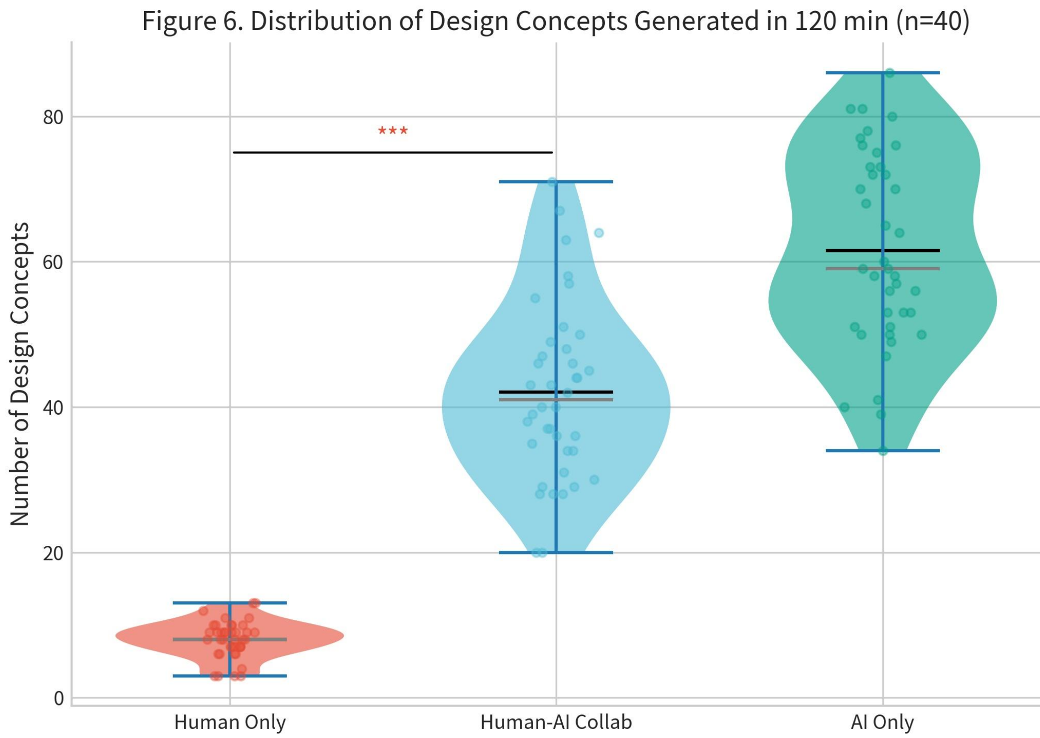

Figure 10. Distribution of the Number of Design Concepts Generated Within 120 Minutes.

Subjective evaluation results from 115 valid participants indicated that the human–AI collaboration (Human–AI Collab) group achieved the highest scores across all evaluation dimensions. Analysis of variance (ANOVA) revealed that the differences between groups were highly statistically significant ($p < 0.001$) (Figures 11 and 12).

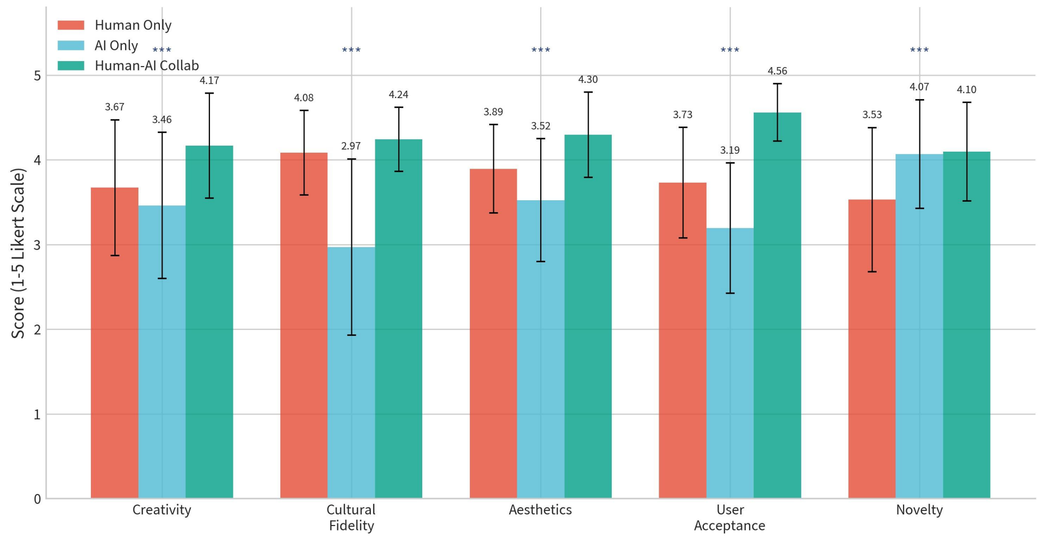

Figure 11. ANOVA Results of Design Evaluation Scores.

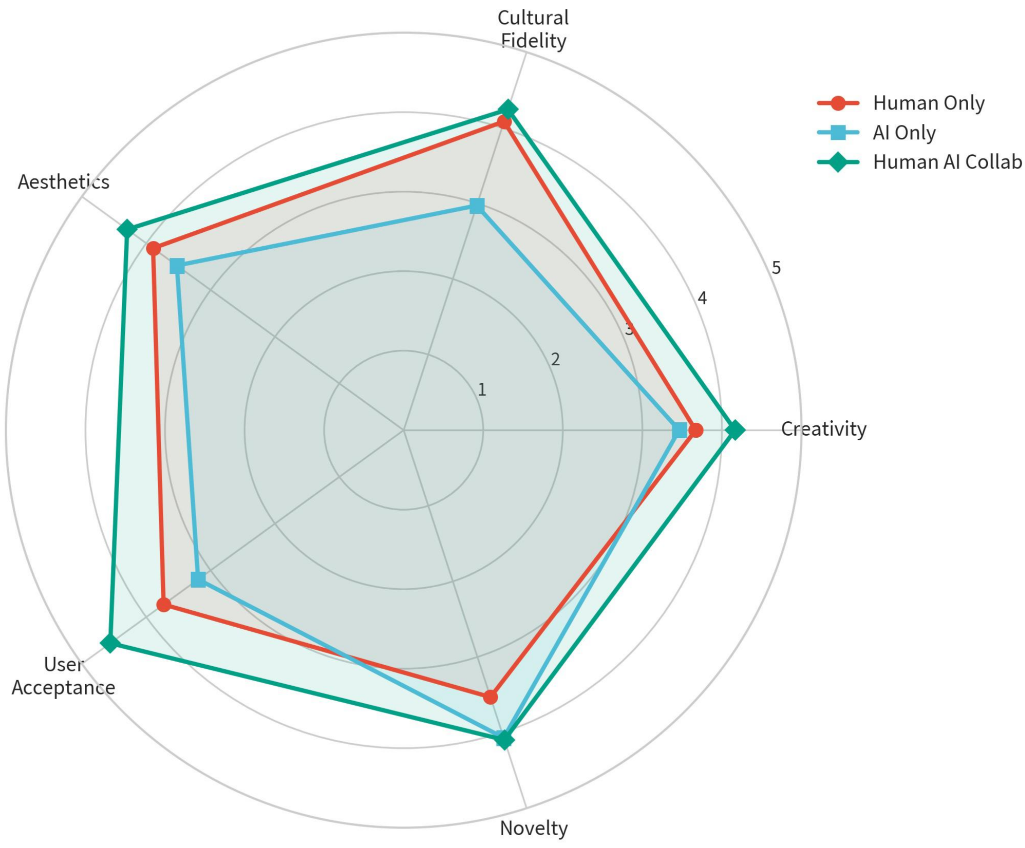

Figure 12. Radar Chart of the Three Groups' Design Concepts Across Five Evaluation Dimensions.

Notably, the purely AI-generated group (without human intervention) scored only 2.91 ± 1.08 on cultural fidelity, exhibiting significantly increased variance. This indicates that, in the absence of human contextual guidance, machines are prone to misplacement of cultural elements. This finding objectively confirms the irreplaceable role of human–AI collaboration in maintaining a balance between the authenticity and innovation of cultural heritage design (Figure 13).

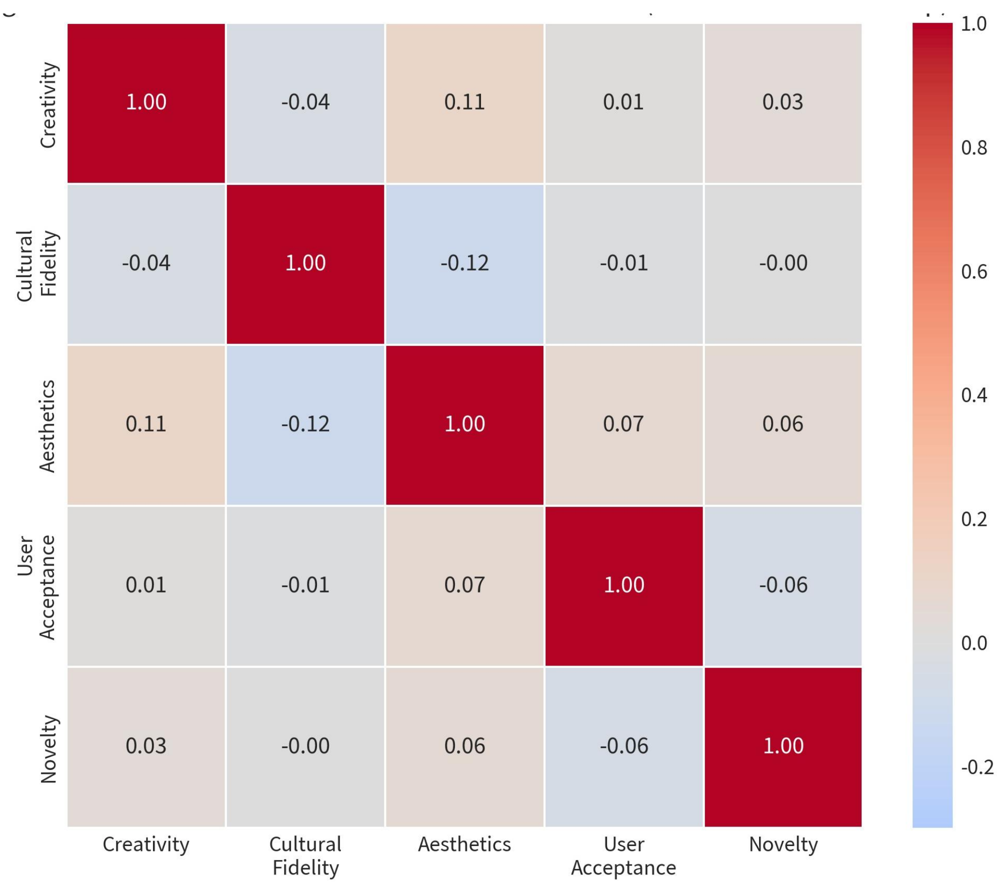

Figure 13. Correlation Matrix of Evaluation Dimensions in the Human–AI Collaboration Group.

6. Discussion

6.1. Cross-sectional Comparison: Technological Empowerment and the Evolution of Traditional Paradigms

A horizontal comparison of the present study's results with existing literature (e.g., Stoean et al., 2024 [2]; Mason et al., 2021 [1]) reveals that the depth of generative AI applications in the cultural heritage domain has surpassed the early "auxiliary tool" positioning. Traditional digital paradigms rely on manual modeling and rule-driven parametric design, with outputs constrained by physical laws and labor costs. This study demonstrates that, through the combination of diffusion models and LoRA fine-tuning techniques, design teams can explore vast parameter spaces in a very short time, achieving a shift from "linear iteration" to "parallel generation." This exponential efficiency gain provides a feasible technological pathway for handling the massive data associated with cultural heritage [20].

6.2. Longitudinal Correlation: From Restoration to Innovation in a Closed Loopc

A close longitudinal logical relationship is observed among the internal results of this study. High-precision virtual restoration (Results 5.2) provides a high-quality data foundation for subsequent innovative design (Results 5.3), while the "cultural hallucination" issues exposed during the innovation phase in turn impose stricter requirements on the purity and annotation accuracy of the upstream model training data. This finding establishes a closed-loop system of "data acquisition → model fine-tuning → generation validation → human correction," validating that, within a design-thinking framework, AI serves not merely as an executor but also as a catalyst for problem reframing [3].

6.3. Attribution of Differences: The Tension Between Cultural Context and Algorithmic Black-Box

The low cultural fidelity scores of the purely AI-generated group in this study contrast with some prior claims of AI omnipotence [21]. A deeper analysis of the underlying mechanisms suggests that this discrepancy is primarily due to the tension between the "black-box" nature of generative algorithms and the context-dependent characteristics of cultural heritage. Cultural heritage is not merely a collection of visual symbols but a composite of history, philosophy, and folklore [22]. Current mainstream models, predominantly pretrained on general internet data, lack an understanding of the deep semantic layers of specific cultures. Consequently, when confronted with design tasks requiring complex metaphors and historical logic, AI is prone to "style patchwork" errors [23]. This attribution underscores the critical importance of involving cultural scholars for "value alignment" in future interdisciplinary research.

7. Conclusion

7.1. Key Findings

This study systematically evaluated the comprehensive effectiveness of generative artificial intelligence in the digital preservation and innovative design of cultural heritage through a mixed-methods approach. The results indicate that generative AI reshapes the workflow of cultural heritage innovation by significantly expanding the design search space and accelerating high-fidelity prototype generation. However, the realization of its core value relies on a human-AI collaboration framework, where human cultural judgment mitigates algorithmic "hallucinations" and ethical risks.

7.2.Research Implications

At the theoretical level, this study extends the boundaries of design-driven interdisciplinary innovation by proposing a cultural heritage design paradigm that positions AI as a "collaborative creator." At the practical level, it provides museums and the cultural creative industry with a validated toolchain and workflow: fully leveraging AI's generative capabilities during divergent ideation phases, while reinforcing expert dominance in convergent evaluation and cultural-semantic mapping phases. This approach enhances commercial transformation efficiency while safeguarding the integrity of cultural heritage.

7.3.Research Limitations

First, regarding scope, the experimental dataset (CHGD-2026) primarily focuses on Chinese traditional cultural heritage (e.g., ceramics and ancient architecture), with limited coverage of other cultural systems, which may affect the generalizability of the conclusions. Second, in terms of methods and data, although LoRA fine-tuning was employed, computational constraints prevented the complete elimination of detail errors in complex historical scene generation, and some long-term interactive experience data remain relatively sparse.

7.4.Future Research Directions

Based on these limitations, future research should focus on: (i) constructing high-quality, multilingual, cross-cultural open-access cultural heritage datasets to train more generalizable domain-specific large models; (ii) developing explainable AI—based generative tools, enabling designers to intuitively understand and intervene in the AI feature extraction process; and (iii) exploring the deep application of generative AI in the dynamic, multimodal reconstruction of intangible cultural heritage, such as traditional music and dance.

References

[1] M. Mason and G. Vavoula, "Digital cultural heritage design practice: A conceptual framework," The Design Journal, vol. 24, no. 3, pp. 385-406, 2021.

[2] R. Stoean et al., "Bridging the past and present: AI-driven 3D restoration of cultural heritage

artifacts,"Journal of Cultural Heritage, vol. 65, pp. 123–135, 2024.

[3] A. Sreenivasan et al., "Design thinking and artificial intelligence: A systematic literature review exploring synergies,"Design Studies, vol. 27, pp. 112–128, 2024.

[4] A. R. Willis and D. B. Cooper, "Computational reconstruction of ancient artifacts,"IEEE Signal Processing Magazine, vol. 25, no. 4, pp. 65–83, 2008.

[5] J. Li et al., "A systematic review of digital transformation technologies in museum exhibitions,"Computers in Human Behavior, vol. 152, 108075, 2024.

[6] J. Wu et al., "Application of GANs in Ancient Architectural Heritage Image Restoration,"Heritage Science, vol. 13, p. 45, 2025.

[7] F. Zhao et al., "GAN-based heterogeneous network for ancient mural restoration,"Heritage Science, vol. 12, p. 117, 2024.

[8] J. K. Fieldhouse et al., "The intersection of artificial intelligence with qualitative or mixed methods research,"Public Health, vol. 238, pp. 104–112, 2025.

[9] Z. Salma et al., "Designing Co-Creative Systems: Five Paradoxes in Human-AI Collaboration,"Information, vol. 16, no. 10, p. 909, 2025.

[10] X. Li et al., "Artificial Intelligence for Sustainable Industrial Design,"Processes, vol. 14, no. 5, p. 779, 2026.

[11] M. S. B. Storeide et al., "A review of implementations of 3D in cultural heritage,"Heritage Science, vol. 11, p. 79, 2023.

[12] R. Quattrini, M. Ferretti, and B. Di Leo, "Combining Digital Heritage and Design Thinking: A Methodological Bridge Between Research and Practice for Inner Areas Regeneration,"Heritage, vol. 8, no. 4, p. 126, 2025.

[13] K. Ghaith, "AI in Heritage: Bridging Tradition and Technology,"International Journal of Educational Innovation, vol. 3, no. 1, p. 4, 2025.

[14] Q. Jia et al., "High-fidelity 3D reconstruction of cultural heritage via super resolution,"Heritage Science, vol. 14, p. 235, 2026.

[15] L. Fang et al., "DCAF-GAN: Enhancing historical landscape restoration with deep learning,"Scientific Reports, vol. 15, p. 12571, 2025.

[16] J. Yu et al., "Heritage Reborn: AI-Driven Style Transfer and Scene Reconstruction," inProceedings of the ACM Web Conference 2025, pp. 3769–3778, 2025.

[17] X. Zhao et al., "Deep learning-driven digitization of traditional crafts and design,"International Journal of Housing Science and Applications, vol. 49, no. 4, pp. 378–390, 2025.

[18] J. Rafner et al., "Agency in Human-AI Collaboration for Image Generation,"Journal of Creativity, vol. 36, no. 2, 10400419, 2025.

[19] A. J. Nashwan et al., "Harnessing Artificial Intelligence for Qualitative and Mixed Methods in Research,"Cureus, vol. 15, no. 11, e48560, 2023.

[20] V. Del Vecchio et al., "Designing Innovative Digital Solutions in the Cultural Heritage Sector,"Applied Sciences, vol. 15, no. 9, p. 4935, 2025.

[21] Y. Chen et al., "The impact of AI-generated technologies-driven digital cultural heritage on user experience,"Heritage Science, vol. 13, p. 214, 2025.

[22] Y. Zheng et al., "A Natural Language Processing Model for Automated Organization and Analysis of Intangible Cultural Heritage,"International Journal of Asian Business and Information Management, vol. 15, no. 1, pp. 1–18, 2024.

[23] Y. Wang et al., "Visual style transfer for cultural heritage: A comprehensive review of techniques and applications,"Journal of Cultural Heritage, vol. 72, pp. 88–105, 2025.