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RESEARCH OF AIGC AND HUMAN ART PICTURE CREATION BASED ON PANOFSKY'S THREE-LEVEL ICONOLOGY FRAMEWORK

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Abstract:

This study investigates the narrative, symbolic, and cultural differences between AI-generated imagery (AIGC) and human-created realist artworks through Panofsky's three-level iconology framework. The research identifies gaps in semantic logic, cultural depth, and symbolic coherence within AIGC outputs while establishing a systematic analytical model suitable for cross-method evaluation. By integrating qualitative iconological interpretation, computational visual analysis, and expert review, this paper contributes an evaluative paradigm that addresses contemporary challenges in AI-driven visual culture. Findings highlight significant fragmentation in narrative cohesion and symbolic misalignment in AIGC compared with human artworks, emphasizing the importance of cultural semantic grounding in future AI development.

Keywords:

AIGC; Iconology; Panofsky; Narrative Art; Human - AI Comparison

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Introduction

The rapid development of Artificial Intelligence Generated Content (AIGC) has reshaped visual art creation, prompting the academic community to explore its artistic value compared to artificial works. Although existing literature has explored the technical capabilities of AIGC, there are still gaps in using theoretical frameworks such as the Panofsky image model for systematic comparisons. This study analyzes AIGC images through Panofsky's three-layer framework - formal, representational, and intrinsic - to elucidate their similarities and differences with human art, in order to address these gaps. The research focuses on the limitations of AIGC in conveying emotional depth, cultural symbolism, and historical context.

The scope is limited to visual arts, especially image creation. The research question is: What are the differences between AIGC and images created by humans at Panofsky's three levels? The purpose is to provide a theoretical framework for evaluating the artistic value of AIGC and its interaction with human creativity, and to provide information support for future artistic and technological cooperation. This research not only addresses a critical gap in understanding AIGC's artistic potential but also lays the groundwork for innovative applications in digital art, design education, and cultural heritage preservation.

Literature Review

Theoretical Basis for Analyzing AIGC Images

AIGC relies on multiple generative architectures, including GANs, diffusion models, VAEs, autoregressive models, and Transformer-based systems. These models learn texture, structural features, and semantic patterns through deep neural networks, enabling high-quality image synthesis. The theoretical foundations of AI *image* generation originate from machine learning and deep learning, particularly neural network architectures that support multimodal semantic‑visual mapping. ANNs and CNNs are responsible for learning hierarchical visual features; GANs continuously improve image realism through the adversarial mechanism between the generator and the discriminator; diffusion models learn data distribution through a two-way process of "noise addition and denoising," and are the core of current mainstream text-to-image generation systems (such as Stable Diffusion and DALL· E); VAEs achieve controllable and stable image generation through latent space structures; and Transformers make cross-modal semantic mapping between text and vision possible. Under this technological framework, the AIGC production process has also formed a new form of digital labor. Human creators contribute through prompt design, selection, modification, and aesthetic judgment. As a result, the AIGC process functions as a human‑AI co-creation model in which the machine generates visual outputs while humans provide semantic and cultural guidance. Recent studies by Smith et al. (2023) and Lee (2024) have directly compared AIGC outputs with human-created artworks, highlighting differences in emotional resonance and cultural specificity. However, these studies lack a systematic framework for cross-level analysis, which study addresses through Panofsky's tripartite model.

Enhance The Artistic Quality of AIGC Through the Panofsky's Framework

While AIGC, utilizing deep generative systems such as GANs, diffusion models, and Transformers, can generate high-quality, realistic images, its outputs often remain at the level of texture and composition, lacking deeper cultural and symbolic meaning. Therefore, it becomes necessary to introduce Erwin Panofsky's three-layer image analysis theory.This theory shifts the analytical focus from visual representation to symbolic interpretation and

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cultural context, allowing us to move beyond simply discussing whether AI can "draw" images, and instead assess whether its generated content possesses symbolic meaning, aesthetic depth, and cultural resonance..Improving the artistic quality of AIGC can be systematically examined using Panofsky's three-layer image analysis framework.

At the formal level, corresponding to pre-image perception, the focus is on visual quality, realism, and aesthetic appeal. Recent advancements combining diffusion models, generative adversarial networks (GANs), and StyleAdapters have made it possible to generate high-fidelity and stylistically flexible images. However, formal excellence requires not only realism but also aesthetic judgment, highlighting the necessity of human-computer interaction evaluation.

At the content level (corresponding to iconographic analysis), AIGC must interpret complex narratives, themes, and cultural symbols. Applications in digital content creation, such as visualizations of the Classic of Mountains and Seas, game character art, and educational design, demonstrate AI's ability to accelerate iteration and stimulate creative exploration.

At the interpretative level (corresponding to iconographic interpretation), AI faces challenges in conveying human emotions, cultural identity, and philosophical depth. Integrating cultural context and interdisciplinary knowledge into multi-layered models is crucial.

Future research should strengthen human-computer collaboration, develop multimodal interaction systems, and establish an evaluation framework that can capture cultural nuances, originality, and ethical considerations, thereby guiding the systematic development of AI art within Panofsky's theoretical framework.

Reconstruction Of the Relationship Between the Creative Subject

The core of human machine collaboration in the field of AIGC creation is the symbiotic model of "human designer+algorithm generator". Taking tools such as Adobe Firefly as an example, designers can iteratively optimize prompt words to guide the generation direction, build a "conception generation feedback" loop system, and achieve two-way interaction in the creative process. Related research shows that when professional artists collaborate with AI, their creative efficiency can be improved by 40%, while also breaking through traditional creative limitations and expanding the boundaries of style exploration. However, the issue of creative ownership has sparked numerous legal and ethical controversies. The first case of AI generated image infringement heard by Beijing Internet Court in 2024 clarifies the principle that "input instructions do not constitute creation", but does not define the core issue of AI training data copyright ownership. In addition, the academic community has proposed the theory of "digital labor", which believes that AI models, by absorbing a large number of human art works to complete training, inherently have the suspicion of "implicit plagiarism", further highlighting the complexity of ownership disputes.

Human AI Collaboration (HAIC)

Human – AI collaboration (HAIC) frameworks emphasize complementarity between human creativity and machine computation. In design and visual arts, HAIC typically involves problem definition, prompt engineering, AI generation, evaluation, refinement, and iterative optimization. These workflows demonstrate that AI is most effective when integrated as an assistive or exploratory partner rather than an autonomous creator.Empirical studies show that

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collaboration with AI can improve creative efficiency and expand stylistic diversity. However, high-quality outcomes depend on human interpretation, aesthetic judgment, and contextual understanding—capabilities that AI cannot independently replicate. As a result, the creative process becomes a dynamic loop of human intention and machine suggestion, reshaping traditional notions of authorship and artistic agency.

AI Workflow Creation Logic

The AI art creation workflow typically consists of four core stages, forming a closed loop for iterative optimization. The first step is data collection and preprocessing, which requires collecting a large amount of art data, cleaning, labeling, and other operations to form a high-quality dataset, laying the foundation for subsequent model training. Continuing into the model training and optimization phase, it is necessary to select suitable generative models such as GAN, VAE, or Transformer, conduct training using preprocessed data, and optimize the generation effect by continuously adjusting parameters. Next is generation and evaluation, using the trained model to generate new works of art, and then evaluating the quality and artistic quality of the works through manual or algorithmic means. Finally, manual adjustment and review are carried out to modify the AI generated works to fit human aesthetics, while ensuring that the content is in compliance with ethical and legal norms. Through iterative cycles at each stage, AI's creative ability and artistic quality of its works continue to improve.

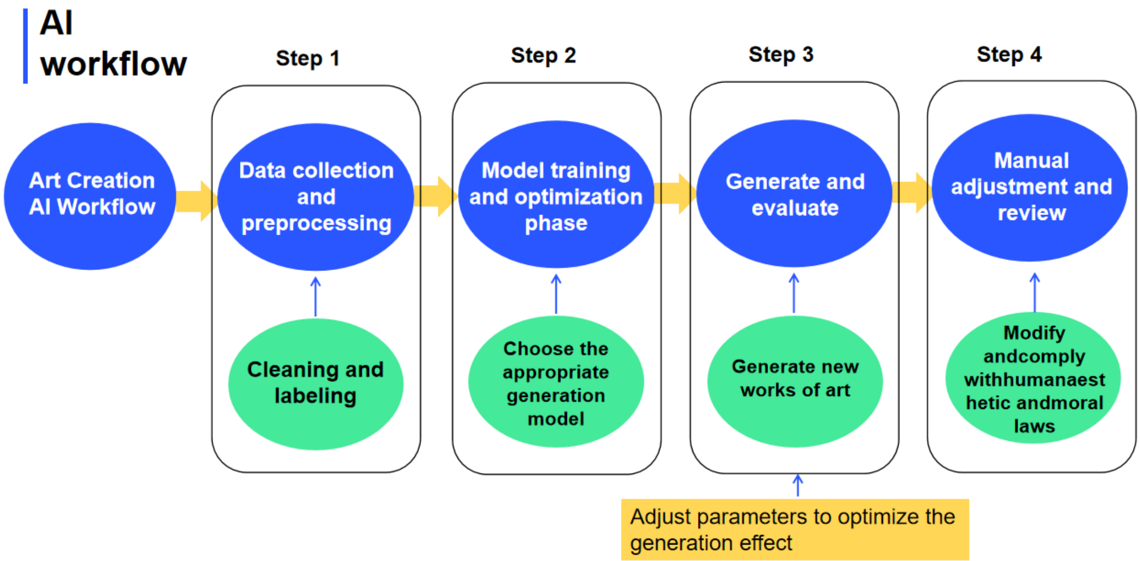

Figure 2: Four steps of AI workflow

Source: Data from this study

AI Workflows in Creative Industries

Recent academic research describes AIGC as a "super symbol processor," capable of rapidly recombining visual, linguistic, and cultural symbols through large-scale statistical learning. While this symbolic capability can enhance creative workflows with unprecedented efficiency–including content generation, style transfer, personalization, and market forecasting in fields such as film, fashion, games, and advertising–it also risks reducing creativity to pattern replication, thereby weakening the human interpretive, emotional, and ethical dimensions that give depth to cultural production. Scholars warn that without deliberate "humanistic balance," AI-driven symbolic recombination could exacerbate dataset bias, smooth out cultural nuances, accelerate aesthetic homogenization, and marginalize human creators in a reconstructed labor

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ecosystem. Maintaining this balance requires integrating human judgment into AI workflows, ensuring transparency of model sources, protecting author identity and cultural rights, and cultivating AI literacy among creators, so that human values－rather than algorithmic efficiency－remain the cornerstone of cultural meaning construction. As the creative industries shift towards a human-machine hybrid collaborative model, ethical governance must continuously evolve to protect originality, cultural diversity, and equitable working conditions, while leveraging the symbolic capabilities of AI to enhance, rather than replace, human creativity.

Controversy Over the Ownership of Creative Works

AIGC's creative ownership is deeply mired in a dual dilemma of legal ambiguity and ethical disputes. The first AI image infringement case in the Beijing Internet Court in 2024, and the copyright case of the United States' "The Nearest Entrance to Paradise" in 2023, both denied the demand for pure prompt words to claim copyright, but did not solve the copyright problem of training data. Moreover, China, the United States and Europe had a split perception of "human ingenuity" - China recognized human creative intervention in AI, the United States refused to register the copyright of pure AI works, and the European Union required to disclose the copyright situation of training data. There was also a paradox of the legitimacy of training data.

Ethically speaking, the theory of "digital labor" points out that AI training devours copyrighted works, which is an implicit exploitation of human intellectual achievements. The lawsuit by American artists against Stability AI highlights the difficulty for original creators to protect their rights, and AI imitation of artistic styles also threatens the uniqueness and cultural diversity of human creation. The key is to establish a "creative contribution evaluation system", clarify the allocation of human-machine rights, and balance innovation protection and technological development.

Creative Analysis Combining AIGC And AI Workflow Under a Three-Tier Framework

This study adopts Panofsky’s three-layer image science framework—pre-iconographic description, iconographic analysis, and iconological interpretation—to systematically investigate AIGC-enabled human–computer collaboration in design creativity.

At the pre-image level, the focus is placed on documenting visual elements and human–AI interaction trajectories. AIGC systems such as Adobe Firefly can rapidly output diverse design variations in product styling or cultural-tourism visualization; therefore, differences in composition, texture, and stylistic vectors must be recorded alongside designers’ prompt iterations, parameter adjustments, and eye-tracking data, forming a quantifiable corpus of “co-creation evidence” (Guo et al., 2023).

At the image-analysis level, thematic and symbolic structures are examined through computational feature extraction and expert-validated coding—such as identifying Ming-style furniture motifs (e.g., mortise-tenon joints, curved silhouettes) or regional cultural symbols in Shenyang Shenbei tourism design. These analyses reveal how AI evolves from a generative tool to a co-creation partner capable of proposing functional–aesthetic alternatives (Liao & Wang, 2024).

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At the explanatory level, the study interrogates AIGC's broader cultural and ethical implications, including its role in shifting creative paradigms from individual inspiration to model-driven ideation, its potential in sustaining cultural heritage—particularly in furniture innovation (Wang et al., 2024)—and its associated risks of copyright ambiguity and algorithmic bias. A six-step workflow—requirement analysis, prompt engineering, AI generation, evaluation, modification, and iterative optimization—is validated through pilot experiments in Ming-style furniture design and Shenyang tourism visualization, linking classical visual theory with contemporary AIGC practice.

Research Gaps and Future Directions

Despite rapid progress, substantial gaps persist in the academic understanding of AIGC image generation:

Semantic logic: Models still struggle with multi-figure interaction, causal relationships, spatial consistency, and complex narrative scenes. Semantic contradictions remain common, limiting the reliability of AIGC in domains requiring precision.
Creativity and personalization: AI often recombines patterns rather than producing genuinely original ideas. Current systems lack mechanisms for embedding user-specific styles or long-term preference memory, resulting in limited personalization and creative novelty.
Cultural and emotional expression: Training data biases lead to uneven or distorted cultural portrayals, particularly concerning minority or non-Western contexts. AI lacks the capacity to express emotional depth or culturally grounded symbolic meaning.
Security and collaboration: AIGC raises risks related to misinformation, forgery, and unclear authorship. Detection tools, governance frameworks, and cross-border regulations remain insufficient to manage these issues effectively.

Summary

The literature indicates that AIGC has significantly advanced technically and is increasingly integrated into artistic production. However, when assessed through Panofsky' s three-level framework, its limitations become evident: strong formal capabilities coexist with shallow symbolic representation and insufficient cultural depth. Human‑AI collaboration presents new possibilities for creativity, yet also introduces complex ethical and governance challenges. Addressing gaps in semantic coherence, cultural meaning-making, and authorship will require interdisciplinary research, improved datasets, and new evaluative frameworks. Panofsky' s model thus provides not only a theoretical lens for examining current AIGC but also a foundation for future inquiries into the evolving relationship between technology, culture, and artistic creation.

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