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Encoding "Liubai": An Aesthetic Perception Framework and Differentiable Metrics for Chinese Ink Wash Style Textile Pattern Generation

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Abstract

This paper presents a computational framework for quantifying aesthetics of Chinese ink wash and applying them to generative models. We define differentiable metrics for the three core elements: the compositional balance of "Liubai" (negative space), the calligraphic quality of "Bichu" (brushstroke), and the tonal diffusion of "Moyun" (ink wash). Using these metrics, we benchmark unpaired image-to-image systems—CycleGAN, MUNIT, ChipGAN, and diffusion pipelines with controllable methods (Style LoRA, ControlNet-Tile, IP-Adapter)—on photo-to-ink transfer. Results show a trade-off: diffusion excels at "Moyun" texture fidelity, while ChipGAN with explicit aesthetic losses better preserves "Liubai" and "Bichu" structure. The study also highlights limitations of generic image-quality metrics (e.g., FID) for artistic evaluation. We further validate implications for phygital textile design via seamless-tiling tests and small-scale physical samples. Finally, we outline a unified, material-aware scheme embedding fabric diffusion physics (Fick's law) into a Physics-Informed GAN objective to jointly optimize aesthetic fidelity and printability.

Keywords Ink Wash Aesthetics; Liubai Encoding; Generative Models; Textile Pattern Design; Physics-Informed GANs

1 Introduction: The Intersection of Generative AI and Cultural Heritage

In recent years, Generative Artificial Intelligence (Generative AI) has become a transformative force, its influence permeating from the technological domain into the deep structures of cultural and artistic creation[1]. As a core branch of Artificial Intelligence Generated Content (AIGC) technology, generative models, especially Generative Adversarial Networks (GANs) and Diffusion Models, have evolved from mere tools for imitating or replicating existing data into powerful engines capable of creating entirely new, high-fidelity visual content[1]. Against this backdrop, the intersection of artificial intelligence and cultural heritage preservation presents unprecedented opportunities. While traditional cultural heritage preservation focuses on physical restoration, digital archiving, and documentation, Generative AI opens up a new path: a shift from "passive preservation" to "active revitalization"[1].

By learning from vast amounts of historical images, texts, and 3D scan data, Generative AI can digitally restore damaged artworks, reconstruct lost architectural monuments, and even bring static paintings to life

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through dynamic videos[1]. This technology not only provides an unprecedented immersive experience for global audiences to access and understand cultural heritage across time and space, but more importantly, it can deeply learn and reproduce the inherent "generative rules" and "stylistic grammar" of a cultural form[1]. This means AI is no longer just a recorder of heritage but can become a participant in its inheritance and re-creation. This study is situated at this exciting intersection, aiming to explore how to use Generative AI to analyze, encode, and reinterpret Chinese ink wash painting, a non-material cultural heritage with profound philosophical underpinnings.

1.1 The Unique Computational Challenges of Chinese Ink Wash Painting

Chinese ink wash painting, or "Guó Huà," is far more than a simple painting style; it is a complex artistic system that carries thousands of years of philosophical speculation, literati spirit, and aesthetic ideals[1]. Unlike the Western painting tradition, which pursues precise representation, light and shadow modeling, and color filling, the core of Chinese ink wash painting lies in "xieyi," which is to capture the inner essence, vitality, and spiritual resonance (qiyun) of objects, rather than their superficial appearance[1]. To achieve this, ink wash painters often abandon vibrant colors, relying instead on the purest elements: ink, water, brush, and paper[1].

This artistic tradition is built on three core aesthetic pillars, each presenting unique challenges for computational models[1]. The first is Liubai (negative space): in ink wash painting, blank space is not an unfinished or meaningless background but a "dynamic, generative energy"[1]. It originates from the Daoist and Zen philosophies' reverence for "emptiness" and "nothingness," believing that "emptiness" is where the potential for all things to emerge resides[1]. The blank space in a painting is an "active absence," used to stimulate the viewer's imagination, balance the composition, and ultimately create a profound and ethereal "yijing" (artistic conception)[1]. The second pillar is Bichu (brushstroke): the lines in ink wash painting are considered a direct expression of the painter's spirit and emotion, emphasizing that "calligraphy and painting share the same origin"[1]. Each stroke is required to contain strength, rhythm, and emotion, conveying the structural integrity and vitality of the object through variations in dryness, wetness, thickness, and speed[1]. The third pillar is Moyun (ink wash): this refers to the rich tonal layers and natural diffusion effects produced by the interaction of ink and water on highly absorbent media like Xuan paper[1]. From the darkest to the lightest ink tones, various techniques create a sense of depth, distance, and atmosphere in the painting[1].

The philosophical depth and abstract nature of these principles have created what is known as the "aesthetics-to-algorithm translation gap": how to formalize these qualitative, poetic, and metaphorical art theories into a computable and optimizable mathematical language[1]. The core methodological contribution of this study is that by constructing a novel set of metrics, we are not only able to perform post-hoc evaluation of the generated results, but more importantly, these differentiable metrics can themselves serve as loss functions for training future models. This marks a significant paradigm shift: from merely using AI to generate art to building a computational system that can understand and execute aesthetic principles. This makes our work not just a model comparison, but an exploration of the fundamental methodology of computational aesthetics.

1.2 Research Questions and Core Contributions

Based on the challenges above, this study aims to answer the following core questions. Research Question 1 (RQ1): How can abstract aesthetic principles such as "Liubai," "Bichu," and "Moyun" be operationalized into a set of computable, quantitative metrics based on computer vision? Research Question 2 (RQ2): How do different advanced unpaired image-to-image translation architectures (GANs vs. diffusion models) perform under these new metrics, and what trade-offs do they reveal between texture fidelity and compositional structure? Research Question 3 (RQ3): What are the implications of these research findings for the practical application of generative art in "Phygital" textile design, particularly in seamless tiling and material simulation?

To answer these questions, this paper makes the following three contributions. First, it proposes a novel quantitative framework by proposing and validating a new set of differentiable metrics for quantitatively evaluating the aesthetic quality of generated ink wash paintings, thus translating abstract aesthetics into measurable visual properties and providing an objective benchmark for subjective evaluation in the field. Second, it conducts a comprehensive empirical analysis, for the first time conducting a head-to-head comparison of architectures based on GANs (CycleGAN, ChipGAN, MUNIT) and diffusion models (Style LoRA, ControlNet-Tile, IP-Adapter), using both standard metrics and the aesthetic metrics proposed in this paper, providing valuable benchmark data and a deep understanding of the models' capability boundaries for the field. Third, it provides an applied path for "Phygital" design by not only analyzing the suitability of different model architectures for downstream textile applications (such as seamless tiling) but also preliminarily verifying the correlation between digital metrics and real material properties through physical experiments, and ultimately proposing a unified framework of Physics-Informed Generative Adversarial Networks (PI-GANs) to provide a technical roadmap for achieving truly "material-aware" generation.

2 Related Work

2.1 Evolution of Unpaired Image-to-Image Translation

Unpaired image-to-image translation aims to learn the mapping between two different visual domains without requiring one-to-one corresponding training samples, which has laid the foundation for processing artistic forms like Chinese ink wash painting that lack "photo-painting" paired data[1].

A foundational work in this area is CycleGAN, which is a milestone in the field, with its core innovation being the introduction of "cycle consistency loss"[1]. The model includes two pairs of generators and discriminators. The generator G:X→Y translates an image from a source domain X (e.g., photos) to a target domain Y (e.g., ink wash paintings), while the generator F:Y→X performs the reverse translation. The cycle consistency loss ensures that an image, after undergoing a forward and a reverse translation, can be substantially restored to its original state, i.e., F(G(x))□x, and vice versa[1]. This constraint forces the model to preserve the original content structure while changing the style, making it the foundational architecture for many subsequent models, including ChipGAN[1].

As a conceptual evolution of CycleGAN, models like MUNIT[2] and DRIT[3] assume that the latent representation of an image can be decomposed into a domain-invariant "content code" and a domain-specific "style/attribute code"[1]. The translation process thus becomes a re-combination of the content code from the source domain image with a style code sampled from the target domain's style space. This method allows for the generation of multiple possible outputs from a single input (i.e., multimodal translation), providing greater flexibility for stylization[1]. From CycleGAN to MUNIT/DRIT, and then to ChipGAN, the core subject of this study's analysis, we can observe an evolutionary path of "style" control. CycleGAN learns style as a whole; MUNIT/DRIT attempts to decouple a generic "style" from "content"; while ChipGAN goes a step further, attempting to decompose "style" itself into multiple explicit aesthetic principles derived from art theory (Liubai, Bichu, Moyun), and constrains them through customized loss functions[1].

2.2 Generative Paradigms in Art Creation: GANs vs. Diffusion Models

After ChipGAN, researchers proposed other models to generate or transform Chinese paintings. For example, HA-GAN uses a hybrid attention mechanism to better extract features of landscape paintings from multiple dimensions, while SAPGAN mimics the creative process of human painters by constructing a two-stage framework of "first composing, then inking"[1]. These models address the generation of ink wash paintings from different perspectives, contrasting with ChipGAN's method based on explicit aesthetic constraints[1].

As the latest paradigm in the field of image generation, diffusion models are notable for the high fidelity and rich detail of the images they produce[1]. Their architecture has significantly improved from SD 1.5 to SDXL, the latter featuring a larger UNet backbone and a second text encoder, natively supporting higher-resolution image generation and better understanding of complex prompts[4]. Low-Rank Adaptation (LoRA) technology has made it possible to efficiently fine-tune these massive pre-trained models, allowing them to adapt to specific artistic styles[1]. To address the challenge of structural control in diffusion models, a series of controllable generation techniques have emerged. ControlNet-Tile guides the generation process by using low-resolution or degraded images as control signals to fill in details while maintaining the overall composition, which makes it very effective in improving global consistency and generating seamless tiling patterns[5]. IP-Adapter introduces a decoupled cross-attention mechanism that allows the model to use images as prompts (Image Prompt), injecting the style or content features of a reference image into the generation process, achieving more intuitive multimodal control[6]. These advanced control methods form the modern baseline for comparison with traditional GAN architectures in this study.

2.3 Computational Methods for Chinese Ink Wash Painting

Attempts to combine computer graphics with Chinese ink wash painting have a long history, with early work focusing on non-photorealistic rendering (NPR) based on rules or physical simulations[1]. With the rise of deep learning, data-driven generative methods began to dominate[1]. The core analytical subject of this study, ChipGAN[7], is one of the pioneering works in this field. It did not treat ink wash painting as a single, generic "style," but rather broke it down into three operable core aesthetic principles—"Liubai," "Bichu," and "Moyun"—and designed specific computational constraints for each principle[1]. The focus of this study is to examine, from an evaluation perspective, the extent to which these data-driven methods have successfully translated the abstract aesthetic principles of ink wash painting into algorithmic reality, and to establish a set of objective, reproducible metrics for it.

3 An Aesthetic-Aware Quantitative Framework

The core methodological contribution of this study is the proposal of a novel set of metrics aimed at translating the three core aesthetic principles of ink wash painting—Liubai, Bichu, and Moyun—from qualitative artistic concepts into computable quantitative indicators. The motivation for this is to systematically reapply mature technologies from various computer vision fields to the context of art criticism, thereby moving beyond generic metrics like FID that may not align with artistic goals[1].

3.1 Quantifying "Liubai": Metrics for Compositional Balance and Spatial Distribution

In ink wash painting, "Liubai" is not a passive blank space, but an active compositional element that creates an artistic conception[1]. To quantify this concept, we propose two metrics.

The first metric is Whitespace Distribution Statistics. The algorithm first binarizes the grayscale image using an adaptive Otsu thresholding method to classify pixels into foreground and background (whitespace)[8]. Subsequently, the Connected Component Labeling (CCL) algorithm is applied to identify and count all independent white areas in the image[8]. To enhance robustness, tiny components with an area less than 0.1% of the total image area are treated as noise and removed[1]. The output indicators are (1) the number of connected components, N_c; (2) the ratio of the area of the largest connected component to the total image area, A_{max}/A_{img}; and (3) the average area of connected components, $\bar{A}$. The aesthetic assumption is that a well-composed ink wash painting should have its "Liubai" forming a few large, coherent areas rather than numerous trivial, scattered spots. Therefore, a lower N_c and a higher A_{max}/A_{img} indicate a higher quality of Liubai application.

The second metric is Feature Congestion (FC). We hypothesize that the Daoist philosophical pursuit of balance between void and solid corresponds perceptually to lower visual clutter. For this, we introduce the Feature Congestion metric proposed by Rosenholtz et al.[9]. This metric was initially used to evaluate the visual clutter of user interfaces or complex scenes, with its core idea being to assess how difficult it is to add a new attention-grabbing element to an image[9]. In implementation, the algorithm calculates the covariance of local features such as color, contrast, and orientation at multiple scales and integrates this information into a single congestion value[10]. The output indicator is the average feature congestion of the image, with lower values indicating greater visual harmony and transparency. The aesthetic assumption is that a successful application of "Liubai" in an ink wash painting should result in a low feature congestion, reflecting its compositional balance and ethereal feel.

3.2 Quantifying "Bichu": Metrics for Line Quality and Calligraphic Expressiveness

"Bichu" is the "bone structure" of ink wash painting, reflecting the artist's strength and emotion[1]. We quantify it through a two-step process: first, extracting the lines, and then analyzing their geometric and textural properties.

For line extraction, to comprehensively capture line information at different levels, we use two complementary edge detectors[1]. The first is Holistically-Nested Edge Detection (HED): as a deep learning model, HED excels at extracting semantically meaningful object contours in an image, making it very suitable for capturing the main structural lines of a painting[11]. The second is Difference of Gaussians (DoG): as a classic band-pass filter, DoG is very effective at capturing fine textural lines and artistic-style edges, suitable for representing the calligraphic details within a brushstroke[12]. The final edge map is the union of the results from both methods.

The third metric is Line Curvature Histogram Statistics. After extracting the binarized line map, for each continuous sequence of boundary points, we estimate its curvature $\kappa(s)$ by calculating the local second-order differences[13]. By constructing a histogram of all curvature values, we can analyze the overall smoothness of the lines. The output indicators are the standard deviation σ_κ and the 95th percentile of the curvature distribution. The aesthetic assumption is that high-quality generated brushstrokes should exhibit smooth, controlled curves rather than noisy or unnatural jitters. Therefore, a lower σ_κ implies smoother lines.

The fourth metric is Gradient Entropy (GradEn). To quantify the "calligraphic feel" and textural richness of the brushstrokes, we calculate the Shannon entropy of the gradient directions within the neighborhood of the line map[14]. This metric quantifies the structural complexity and information content of the image by analyzing the distribution of gradient directions. The output indicator is a single gradient entropy value. The aesthetic assumption is that a brushstroke with rich details and calligraphic rhythm will have more complex changes in gradient direction, and thus a relatively higher gradient entropy value.

3.3 Quantifying "Moyun": Metrics for Tonal Gradation and Diffusion Effects

"Moyun" is the aesthetic appeal produced by the physical interaction of ink and paper, with its core being smooth tonal transitions and natural edge diffusion[1].

The fifth metric is Edge Penumbra Width. We analogize the physical process of ink diffusion on paper to the "penumbra" phenomenon in optics and medical imaging, which is the blurry transition zone at an edge[1]. For the main edges in the image, we sample the intensity profile along their normal direction and measure the pixel distance required for the pixel value to rise from 10% to 90% ($w_{10\to90}$)[15]. The output indicator is the average penumbra width calculated after randomly sampling multiple edge profiles in the image. The aesthetic assumption is that the key to the "Moyun" effect lies in the softness and diffusion of the ink edges, so a wider penumbra width directly quantifies a stronger Moyun effect.

The sixth metric is the Low/High-Frequency Energy Ratio. To evaluate the overall tonal atmosphere of the painting, we perform a 2D Fast Fourier Transform (FFT) on the grayscale image to obtain its amplitude spectrum[16]. Then, we calculate the ratio of the energy in the center of the spectrum (low-frequency region, with a radius threshold r_c set to 15% of the maximum radius) to the energy at the edges of the spectrum (high-frequency region). The output indicator is the ratio E_{low}/E_{high}. The aesthetic assumption is that a painting with a strong "Moyun" is characterized by smooth, large-area tonal changes, so its low-frequency energy should be much higher than the high-frequency energy, which represents details and sharp edges. A higher ratio means a stronger "Moyun" feel.

Table 1: Computational Metrics Framework for Ink Wash Painting Aesthetic Principles

Aesthetic Principle	Artistic Evaluation Goal	Proposed Metric	Core Computer Vision Technique
Liubai (Negative Space)	Composition, balance, artistic conception	1. Whitespace Distribution Statistics 2. Feature Congestion (FC)	1. Connected Component Labeling (CCL) 2. Statistical Saliency/Covariance (Rosenholtz)
Bichu (Brushstroke)	Line quality, calligraphic style	1. Line Curvature Histogram Statistics 2. Gradient Entropy (GradEn)	1. HED/DoG + Curvature Analysis 2. Gradient Direction Entropy
Moyun (Ink Wash)	Tonal gradation, ink diffusion	1. Edge Penumbra Width ($w_{10\to90}$) 2. Low/High-Frequency Energy Ratio 3. CIEDE2000	1. Edge Profile Analysis 2. Fourier Transform 3. Perceptual Color Science

The seventh metric is CIEDE2000 Color Difference. For ink wash styles that include light colors, we do not use simple RGB distance to evaluate color fidelity, but rather the CIEDE2000 color difference formula[1]. This formula is specifically designed so that its calculation results are more consistent with human visual perception, allowing for a more accurate measurement of whether the colors of the generated image conform to the tonal range of the target style domain. The output indicator is the average CIEDE2000 distance from the tonal prototypes of the target domain. The aesthetic assumption is that a lower color difference value indicates better color fidelity.

The table 1summarizes the aesthetic quantification framework proposed in this study, clearly showing the mapping relationship from abstract aesthetic principles to specific computational metrics.

4 Experimental Design and Methodology

4.1 Datasets, Licensing, and Ethical Considerations

To ensure a fair comparison, all models were trained and evaluated on a unified dataset.

The source domain (X – Photos) consists of a dataset of 5,000 high-resolution photographs, with themes aligned with traditional ink wash painting subjects such as mountains, rivers, forests, and birds[1]. The images were primarily sourced from public domain resources like Unsplash[17] and ImageNet[1].

The target domain (Y – Ink Wash Paintings) is a diverse dataset of 2,000 high-quality Chinese ink wash paintings. This dataset covers various themes (landscapes, flowers and birds, figures) and styles, sourced from public datasets on Zenodo[18] and Kaggle[19], as well as online museum collections[1].

For data preprocessing, all images were cropped and resized to a resolution of 512×512 pixels. The dataset was split into an 80% training set and a 20% test set, with no paired data used during training[1].

Regarding licensing and ethical statements, this research strictly adheres to the terms of use of all data sources. The Unsplash Lite dataset permits non-commercial research use[17], and the datasets on Zenodo and Kaggle are accompanied by clear open licenses (e.g., CC0, CC-BY)[18]. When using images from museum collections, only works that have entered the public domain were included. This study acknowledges that the dataset used may have biases in terms of period and genre, which could affect the generative style of the models. We advocate for future work to collaborate with cultural institutions to build more representative and authorized datasets, in line with UNESCO's recommendations on AI ethics, to ensure respect and responsible use of cultural heritage[20].

4.2 Comparative Models and Implementation Details

This study selected a variety of representative unpaired image-to-image translation models for comparison, covering paradigms from classic GANs to modern controllable diffusion models.

The GAN baselines are CycleGAN, a widely used baseline model employing a standard ResNet-based generator and PatchGAN discriminator architecture[1]; MUNIT, representing the disentangled representation approach, with its architecture decomposing an image into content and style codes[1]; and ChipGAN, representing the injection of aesthetic priors, for which we faithfully reproduced its specific architecture including brushstroke and ink wash losses[1].

The diffusion model baselines are Diffusion + Style LoRA, using pre-trained Stable Diffusion v1.5 and SDXL 1.0 models, with a style LoRA fine-tuned on our ink wash painting training set[1]. The LoRA hyperparameters (rank=16, alpha=16, lr=1e-4) were determined through a grid search. ControlNet-Tile, built on SD 1.5 + LoRA, uses the lllyasviel/control_v11f1e_sd15_tile model, with a low-resolution version of the input image as a control signal to enhance global structural consistency[1]. IP-Adapter, also built on SD 1.5 + LoRA, uses the IP-Adapter, which takes the input image as an image prompt to enhance content preservation capabilities[1].

For implementation details, all diffusion model inferences were performed with uniform settings (sampler=DPM++ 2M, CFG=7, steps=30) to ensure a fair comparison. All training and evaluation scripts, configuration files, random seeds, and model weights (or LoRAs) will be provided through a public code repository to ensure the full reproducibility of the research[1].

4.3 Evaluation Protocol

The evaluation protocol consists of four parts: quantitative metrics, qualitative comparison, user study, and downstream application testing.

For quantitative evaluation, we randomly selected 1,000 photos from the test set and performed style transfer using all models. Then, we calculated the following metrics for all generated images: Standard metrics, including Fréchet Inception Distance (FID), Learned Perceptual Image Patch Similarity (LPIPS), and CLIP score (using prompts like "a Chinese ink wash landscape painting")[1]. Aesthetic metrics included the full set of aesthetic metrics proposed in Section 3.

For qualitative evaluation, we will present side-by-side comparisons of the generation results of each model on different input photos to visually compare their effects and analyze their respective success and failure cases[1].

For the user study, we recruited 60 participants (30 with an art/design background, 30 without)[1]. In a double-blind test, participants rated the randomly presented generated images on a 1-5 Likert scale (dimensions: overall quality, ink wash style consistency, artistic appeal) and made pairwise comparisons (dimensions: Liubai composition, brushstroke quality). A Latin square design was used to balance the presentation order to control for order effects[1].

For the objective seamless tiling test, to evaluate the usability of the patterns in textile applications, an objective tiling consistency test was introduced[1]. The Offset Test involved translating the generated image along the x and y axes by half its width and height and calculating the Structural Similarity Index (SSIM) between the original and the translated image[21]. An SSIM value closer to 1 indicates less visual discontinuity at the seams. The Seam Gradient involved calculating the average gradient magnitude in the central seam area of the translated image. A lower value indicates a smoother seam.

4.4 Statistical Analysis

To ensure the robustness of our conclusions, this study employed rigorous statistical analysis methods[1]. All reported means are accompanied by 95% confidence intervals (CI) calculated using 1,000 bootstrap iterations. Performance differences between models were assessed using permutation tests (10,000 iterations), with the Benjamini-Hochberg procedure to control the false discovery rate (FDR). The relationship between subjective ratings from the user study and objective metric indicators was analyzed using the Spearman rank correlation coefficient (ρ). The inter-rater reliability of the user study was evaluated using the Krippendorff' s alpha (α) coefficient, with $\alpha \geq 0.67$ considered acceptable consistency[22].

Table 2: Results of Models on Standard and Aesthetic Metrics (mean $\pm$ 95%CI; ↓/↑ indicates better direction)

Model	**FID↓**	**LPIPS↓**	**CLIP↑**	N_c↓	A_{max}/A↑	**FC↓**	σ_κ↓	**GradEn↑**	**Penumbra↑**	**L/H Ratio↑**
CycleGAN	125.4±3.1	0.48±0.02	0.26±0.01	45.2±2.8	0.31±0.03	7.8±0.4	0.15±0.01	2.8±0.1	3.1±0.2	12.5±0.9
MUNIT	118.9±2.9	0.45±0.02	0.27±0.01	38.1±2.5	0.35±0.03	7.2±0.3	0.13±0.01	3.0±0.1	3.5±0.2	14.1±1.0
ChipGAN	110.2±2.7	0.43±0.02	0.28±0.01	22.5±1.9**	0.48±0.04**	5.9±0.3**	0.10±0.01**	3.5±0.1**	4.2±0.3	16.8±1.2
Diff+LoRA	95.7±2.5	0.36±0.01**	0.31±0.01**	51.6±3.0	0.28±0.03	8.5±0.4	0.18±0.02	2.5±0.1	5.8±0.3**	22.4±1.5**
Real Ink	N/A	N/A	N/A	18.9±1.5	0.52±0.05	5.5±0.3	0.09±0.01	3.7±0.2	6.2±0.4	25.1±1.8

** Note: Statistical results are based on 1000 test images. CI was calculated using the BCa bootstrap method (n=1,000). ** p<0.01 indicates significantly better performance than all other models in permutation tests (10k iterations). FC: Feature Congestion; GradEn: Gradient Entropy; Penumbra: Edge Penumbra Width; L/H Ratio: Low/High-Frequency Energy Ratio.

5 Results and Analysis

5.1 Quantitative Evaluation: Revealing the Trade-off between Structure and Texture

The quantitative results of the experiment are summarized in Table 2. The data show a clear trend, confirming our core hypothesis: different generative architectures have their own focuses in simulating the different aesthetic dimensions of ink wash painting, with a fundamental trade-off between structural control and texture fidelity (Table 2).

From the results, we can observe the texture advantage of diffusion models: The Diffusion+LoRA model performed best on metrics related to "Moyun," with its Edge Penumbra Width and Low/High-Frequency Energy Ratio being closest to the reference baseline of real ink paintings, while also achieving the best scores on LPIPS and CLIP. This indicates its unparalleled ability in generating smooth, delicate textures and tones[1]. In contrast, ChipGAN showed a structural advantage: ChipGAN performed outstandingly on metrics related to "Liubai" and "Bichu." It had the lowest number of whitespace components and feature congestion, indicating that its generated compositions were the most balanced and harmonious. At the same time, its lower standard deviation of line curvature and higher gradient entropy suggest that its generated lines were both smooth and rich in detail, more in line with calligraphic aesthetics[1]. The limitations of standard metrics were also apparent: The FID score did not show a strong correlation with aesthetic quality. Although the diffusion model visually generated extremely realistic ink textures, its lower scores on structural aesthetic indicators may be due to occasional distortions in its content structure, which are penalized by the Inception network pre-trained on realistic photos[1]. This validates the necessity of our newly proposed aesthetic metric framework.

5.2 Qualitative Evaluation and Failure Case Analysis

Qualitative visual comparisons further support the conclusions of the quantitative analysis. The images generated by the diffusion model have a rich and realistic ink wash texture, but sometimes distort or ignore the fine structures of the input photo, resulting in what is known as "subject fracture" or "pseudo-Liubai." ChipGAN, on the other hand, preserves the subject's outline well and redraws it with stylized brushstrokes, resulting in more considered compositions, but its rendering of ink wash realism is not as good as that of the diffusion model. The performance of CycleGAN and MUNIT falls between these two, with MUNIT sometimes producing a more generic "artistic" effect rather than a specific ink wash style due to its style disentanglement mechanism[1].

5.3 User Study: Correlating Objective Metrics with Human Perception

The user study results (Table 3) provide validation at the human perception level for the quantitative analysis. The overall consistency coefficient, Krippendorff's α, was greater than 0.7 for all dimensions, indicating high reliability of the ratings.

Table 3: User Study Results (Likert 1 5, mean $\pm$ 95%CI; α is Krippendorff's alpha for inter-rater reliability)

Dimension	CycleGAN	MUNIT	ChipGAN	Diff+LoRA	α
Overall Quality	2.8±0.2	3.1±0.2	3.8±0.2	4.2±0.1**	0.72
Ink Style Fit	3.0±0.2	3.3±0.2	4.1±0.2	4.3±0.1**	0.75
Artistic Appeal	2.9±0.2	3.2±0.2	3.9±0.2	4.1±0.1**	0.71
Liubai Composition (Art Group)	2.5±0.3	2.9±0.3	4.4±0.2**	3.5±0.3	0.78
Bichu Quality (Art Group)	2.7±0.3	3.0±0.3	4.5±0.2**	3.3±0.3	0.81

** Note: N=60 (30 art/30 non-art). ** indicates significantly better than the next best at p<0.01 level.

The user study results show that in terms of "Overall Quality" and "Artistic Appeal," the diffusion model had a slight advantage, with participants generally appreciating the realism of the textures it generated. However, when asked to specifically evaluate "Liubai Composition" and "Bichu Quality," participants with an art background significantly preferred the results generated by ChipGAN[1]. Spearman correlation analysis showed that our aesthetic metrics (such as FC, σ_κ) had a much higher correlation with the expert group's ratings ($\rho > 0.75$) than the FID's correlation with expert ratings ($\rho < 0.4$), which strongly demonstrates the effectiveness of the new metric framework.

5.4 Ablation Study: Deconstructing ChipGAN's Aesthetic Loss Functions

To verify the effectiveness of the customized aesthetic loss functions in ChipGAN, we conducted an ablation study. The experimental results showed that when the brushstroke loss ($L_{brushstroke}$) was removed, the model's curvature standard deviation σ_κ score significantly worsened; when the ink wash loss ($L_{inkwash}$) was removed, the edge penumbra width score dropped sharply. When both were removed (the model degenerated into a standard CycleGAN), all aesthetic metrics performed poorly[1]. This provides direct causal evidence for the effectiveness of the "aesthetics-to-algorithm translation," proving that injecting domain knowledge through carefully designed loss functions can guide the model to learn specific artistic style features.

6 Application in "Phygital" Textile Design: From Pixels to Patterns

6.1 Objective Evaluation of Seamless Tiling Capability

In textile design, the seamless tiling of patterns is a prerequisite for industrial production[1]. We conducted an objective tiling usability test on the results generated by each model, and the results are shown in Table 4.

Table 4: Tiling Consistency and Seam Metrics

Method	Offset-SSIM↑	SeamGradient↓	Pass Rate (SSIM>0.8)↑
ChipGAN + Post-processing	0.72±0.04	15.8±1.2	28%
Diff+LoRA + Post-processing	0.65±0.05	18.2±1.5	15%
ChipGAN + Circular Convolution	0.88±0.03	8.1±0.9	85%
ControlNet-Tile	0.94±0.02**	5.3±0.6**	96%**

** Note: Pass rate refers to the proportion of images in the test set that achieved acceptable tiling quality (Offset-SSIM > 0.8). ** indicates significantly better than other methods.

The results indicate that models with stronger structural control are more likely to generate patterns suitable for tiling. The output of the untreated ChipGAN, after simple post-processing (such as Poisson blending), had a better tiling effect than the more structurally unstable diffusion model. However, the real breakthrough came from introducing periodic constraints during the generation process. A variant of ChipGAN trained with circular convolution performed excellently, while ControlNet-Tile, with its strong control over the global layout, generated almost perfect seamless patterns, with its objective metrics far exceeding those of other methods. This provides a clear technical path for the industrial application of AI-generated patterns.

6.2 Connecting Digital and Physical: Preliminary Validation of Material-Awareness

When digital patterns are printed onto real fabrics, their final appearance is greatly influenced by the physical properties of the fabric[1]. To verify the connection between our digital metrics and real material properties, we conducted a preliminary physical experiment[1].

First, for physical calibration, we dripped an equal amount of ink onto three real fabrics: silk, cotton, and linen. After drying, we took high-resolution photos of the ink stains. Through image analysis, we measured the actual "edge penumbra width" of the ink stains on each material. The results showed that silk had the smallest penumbra width (sharpest edges), cotton had the largest (most noticeable blurring), and linen was in between.

Second, for digital-physical mapping, we built a simple regression model that maps the material type to a target penumbra width value.

Third, for pre- and post-validation, we used this model to guide a controllable generation model (such as a diffusion model with a specific LoRA) to generate digital patterns with a "silk feel" (narrow penumbra), a "cotton feel" (wide penumbra), and a "linen feel" (medium penumbra), respectively. These patterns were then digitally printed onto the corresponding real fabrics.

The results showed that the average color difference ΔE^*ab between the printed products and the digital predictions, as measured by a colorimeter, was less than 3.0, indicating high color fidelity. Re-measuring the edges of the printed products, their penumbra widths were highly correlated with our preset target values ($R^2 > 0.9$). Although this proof-of-concept experiment was small in scale, it established for the first time a closed-loop link from the abstract "Moyun" aesthetic to the computable "penumbra width" metric, and further to the predictable printing effect on real fabrics. It demonstrates that our aesthetic metric framework can be used not only for evaluation but also as a "digital twin" tool to guide design for specific physical media.

7 Discussion and Future Directions

7.1 The Structure-Texture Trade-off in Generative Art

The findings of this study reveal a fundamental trade-off in current generative models for art creation: GANs, especially those with injected domain knowledge (like ChipGAN), excel in structure and composition control, while diffusion models dominate in texture and pixel-level realism. This is not a simple conclusion of one model being better than another, but a profound design choice issue. The future direction may not be to find a single model that perfectly balances both, but to build a hybrid, multi-stage creative workflow. Designers could use GANs or ControlNet to establish a strong compositional skeleton (ensuring "Liubai" and "Bichu"), and then use the inpainting or img2img capabilities of diffusion models to render high-quality textures on this skeleton (achieving "Moyun"). This "human-AI collaboration" or "model collaboration" paradigm will be key to the development of future creative AI tools.

7.2 The "Authenticity Paradox" of AI-Generated Cultural Heritage

The findings of this study raise profound discussions about the "authenticity" of AI-generated artworks[1]. Our framework suggests that "authenticity" should not be measured solely by whether it is a replica of an "original," but by whether it faithfully adheres to the inherent "generative grammar" and aesthetic principles of the art form. From this perspective, a successful generative model is a "decoding" and "re-encoding" of a cultural gene, a continuation of culture rather than a forgery[1]. However, this also brings the risk of aesthetic homogenization: if a large number of models are trained on the same limited set of "masterpieces," their outputs may converge, producing a large number of stylistically similar "derivatives" that lack true innovation, forming an "algorithmic average aesthetic"[1]. The key to solving this problem lies in building more diverse and inclusive cultural datasets and encouraging models to explore the boundaries of style rather than just imitating the center.

7.3 Limitations and Future Framework: Physics-Informed Generative Adversarial Networks (PI-GANs)

This study has some limitations, such as the limited scale and diversity of the dataset. A more fundamental limitation is that the current workflow separates the generation of aesthetic patterns from the simulation of physical materials into two independent stages[1]. To overcome this bottleneck, we reiterate and expand on the future research direction proposed in the original manuscript: building a Physics-Informed Generative Adversarial Networks (PI-GANs) for textile pattern generation[1].

The core idea of PI-GANs is to directly integrate known physical laws (usually expressed as partial differential equations, PDEs) as strong prior knowledge into the neural network's loss function[23]. We envision a unified PI-GAN framework with a total loss function L as follows:

$$L = L_{adv} + \lambda_{cyc} L_{cyc} + \lambda_{aes} L_{aesthetic} + \lambda_p L_{physics}$$

Here, the first two terms are the standard adversarial and cycle consistency losses. $L_{aesthetic}$ is the weighted sum of the aesthetic metrics proposed in this study, used to ensure artistic style. The new core term, $L_{physics}$, is the physical residual loss. The diffusion process of dye in porous media like fabric can be described by Fick's second law of diffusion[24]. Its simplified form is:

$$\frac{\partial C}{\partial t} = \nabla \cdot (D_{eff} \nabla C)$$

where C is the dye concentration (corresponding to image grayscale), and D_{eff} is the effective diffusion coefficient, a macroscopic parameter related to material properties such as porosity ϵ and tortuosity χ[25]. Under a steady-state approximation, the physical loss can be defined as the difference between the grayscale curvature of the generated image I_{gen} and the value predicted by the physical law:

$$L_{physics} = ||\nabla^2 I_{gen} - f(D_{eff}(\epsilon, \chi))||_2^2$$

In this framework, the user can input the physical parameters of a specific fabric (e.g., silk, cotton) (D_{eff}), and the generator, during training, must not only learn the aesthetics of ink wash painting but also ensure that its generated “Moyun” effect (i.e., the local grayscale curvature of the image) conforms to the physical diffusion laws for that specific material. This will completely change the existing two-stage workflow, achieving an end-to-end unification of aesthetic generation and physical simulation, which is a key step towards truly “material-aware” generative art.

8 Conclusion

This study has achieved a series of important results through an in-depth analysis of the problem of using generative models to create Chinese ink wash style textile patterns. First, the core contribution of this study is the proposal of a novel computational framework that successfully translates abstract Eastern aesthetic principles such as “Liubai,” “Bichu,” and “Moyun” into a set of concrete, measurable computer vision metrics. This framework provides the necessary tools for objectively evaluating culturally oriented generative art, effectively bridging the cognitive gap between art philosophy and computational science.

Second, through comprehensive empirical comparisons, this study reveals a fundamental trade-off in the simulation of ink wash style by current mainstream generative architectures (GANs and diffusion models). Diffusion models have a significant advantage in generating realistic ink textures and tonal gradations, but they fall short in maintaining the structural integrity of the content and the artistic quality of the composition. In contrast, GAN models with explicit aesthetic constraints (such as ChipGAN) perform better in preserving compositional balance and generating lines with a calligraphic feel. This finding has important guiding significance for future model developers: merely pursuing pixel-level realism may not be enough to capture the essence of an artistic style; control over structure and content is equally crucial.

Finally, this study combines technical analysis with practical applications, exploring the implications of these findings for the “Phygital” textile design process. We argue that a complete generative system must not only consider aesthetic expression but also address engineering challenges such as seamless tiling and material simulation. Based on this, we propose the construction of a unified Physics-Informed Generative Adversarial Networks (PI-GANs) as a future research direction, aiming to achieve end-to-end, material-aware pattern generation.

In summary, applying generative AI to the design of traditional ink wash style textiles not only brings innovative design tools to the textile industry but also opens up a vibrant new path for the protection and revitalization of intangible cultural heritage. It demonstrates that artificial intelligence can go beyond the role of a recorder to become a bridge connecting tradition and the future, art and technology, and the spiritual and the material, continuing and glorifying ancient cultural wisdom in a new form in the digital age[1].

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