DIGITAL PRINTMAKING THROUGH AI STYLE TRANSFER

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ABSTRACT

The practice of digital printmaking is changing due to the combination of computational accuracy and cultural and artistic expression, which artificial intelligence is bringing. The neural style transfer and diffusion-based generative models make it possible to transform the local art culture like Madhubani, Ukiyo-e, and Cubist abstraction into the digital format and capture their cultural identity and accepted modern aesthetics. The use of AI in mapping the stylistic textures, compositional rhythm, and symbolic themes onto new content areas makes it possible to produce visually and conceptually stimulating art pieces that do not belong to particular geographic and time frames. This method is flexible, as demonstrated by three comparative case studies. The Madhubani-Geometry Fusion exhibits the ability of the algorithm in maintaining folk symmetry by use of computational patterning; the Ukiyo-e Metallic Transformation displays the process of neural models to recreate the sensory effect of depth and reflection of metallic surfaces and ink; and the Cubist-Textile Hybridization presents the stylistic cross-cultural blending by using CLIP-guided optimization. Such quantitative measures as the Cultural Authenticity Score (CAS), Perceptual Realism Index (PRI), and Style Fidelity prove that algorithmic creativity do not exclude cultural integrity. In addition to the aesthetic innovation, the study highlights the ethical and curatorial issues that arise in the AI art. The integrity in machine-assisted creativity relies on documentation of datasets in the form of transparency, cultural reciprocity and acknowledgment of the authorship. The collaboration of placing the artists, algorithm, and cultural source on the same level of contribution creates a new paradigm of co-authored creativity in which technology becomes a mediator and not a substitute of the human imagination. This combination of ethical conscious, cultural conservation, and computerized art is what constitutes the changing identity of twenty first century printmaking in digital.

Keywords: AI Style Transfer, Digital Printmaking, Neural Networks, Cultural Heritage, Generative Art, Authorship, Computational Aesthetics, Curatorial Ethics, Perceptual Realism

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1. INTRODUCTION

Digital printmaking has become a paradigm practice that guides the haptic culture of analog printing towards the computational creativity of artificial intelligence (AI). Traditionally based on the methodologies of etching, lithography, and screen printing, printmaking has been the nexus of creative exploration and technological development and change. The paradigm shift in the field occurred with the introduction of the digital technologies, in particular, deep learning and neural networks Goodfellow et al. (2020). With artificial intelligence, neural style transfer (NST) and diffusion based generation have created the possibility of transferring the artistic styles, textures, and motifs across digital surfaces, essentially pushing the limits of printmaking beyond its physical limitations. This combination of art and calculation is not only a change of the tools but the redesigning of the creative authorship, the aesthetic value and reproducibility in the art of today. The central concept of AI-driven printmaking is the principle of style transfer a process where an algorithm removes the stylistic qualities of a single image (like brushwork, color palette, or rhythm) and transfers these characteristics to the content of another one Gatys et al. (2015). Introduced by Gatys et al. as the convolutional neural networks (CNNs), this procedure makes it possible to break down paintings that combine syntactic precision with style expressiveness. In digital printmaking, NST enables an artist to redefine the traditional shapes, rethink folk art, or to create the illusion of intricate textual surfaces which would be hard to render manually. In this combination, the digital prints turn out to be hybrid objects that possess both the computational accuracy and human will to them Isola et al. (2017). The creative agency ceases to be confined in the hand of the artist alone but in the creative collaboration of the human intuition and the machine learning systems in an iterative process.

Figure 1

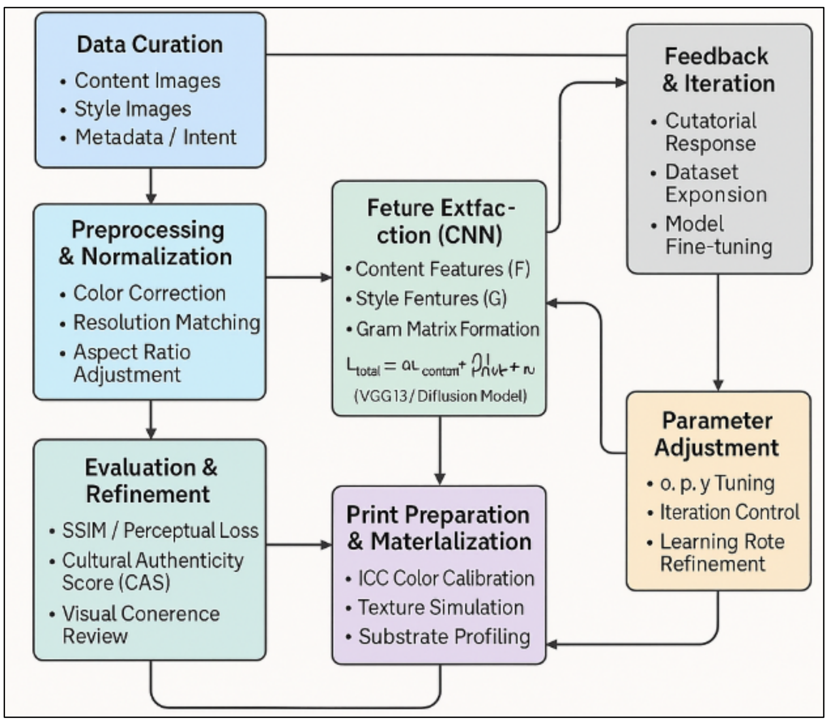

Figure 1 Conceptual Workflow of Ai Style Transfer in Digital Printmaking

The aesthetic aspect of AI-based digital printmaking does not remain in copying or imitating. It provides doors to generative originality, in which machines will synthesize stylistic elements within a wide range of data, generating visual representations which mirror an emergent, non-human aesthetic rationale. These algorithmic metamorphoses permit the re-configuration of visual languages that bring together, such as the austerity of the geometry of Constructivism and the inorganic movement of the traditional textile or folk-art patterns. This recombination of fluids declares the traditional dominance of originality and reproduction Zhu et al. (2017). In conventional printmaking, an edition is prized because it can be reproduced and be reproducible, whereas in AI-based printmaking each iteration has the potential to hold a distinct stylistic meaning and thus the line between the original and its copies is unclear. It is also important that these digital artifacts be made to touch. The current print technologies, including UV-curable inkjet printing, sublimation, and overprinting 3D textures, enable AI-composed artworks to be actually manifested on a wide range of surfaces, including canvas and fine art paper as well as fabric and metallic foils to provide the experience that might be largely missing in art pieces solely presented on screen. Here, the artist filters content and styles images and indicates conceptual intent; images are despecified and sanitized; a style transfer core derives content and style features and combines them under controllable parameters; the generated outputs are refined through coherence, readability and cultural authenticity; and ultimately they are sent to print through color management Hicsonmez et al. (2020), substrate profiling and edition planning. There is also an accentuation of an archival and feedback cycle in the figure, with the response of curators and audiences, as well as new scan and source, into the growth of data sets and the improvement of the models. The use of AI in printmaking thus brings up deep philosophical, ethical concerns on the topic of authorship, ownership, and the ontology of the artwork itself. The aesthetic decision-making process split in the human and the machine results in the collaboration of the creativity and not in the isolated activity. The artist is a less monolithic, more of a system designer, constrainer and curatorial judge, as he or she acts, as captured in the working system of Figure 1. This is a changing discussion of a larger cultural shift to the posthuman aesthetics, where art is not created by the technology but is co-evolving with it Elgammal et al. (2017), Al-Khazraji et al. (2023). Therefore, AI style transfer in digital printmaking does not substitute the artist but rather redefines the very idea of creating printmaking with the new realm of computational poetics and visual synthesis.

2. HISTORICAL AND THEORETICAL FOUNDATIONS

Figure 2

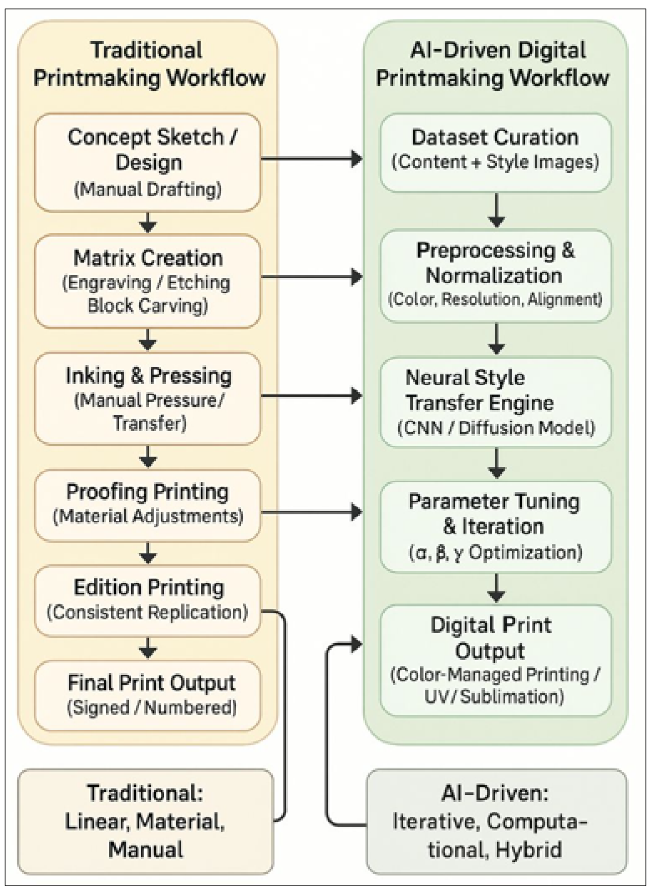

Figure 2 Traditional vs AI-Driven Printmaking

The historical development of printmaking is closely connected with the technological mediation development in art. Since the century of tactile art of woodcuts, engravings, and and etchings (fifteenth century), the experimental serigraphs and photo-mechanical prints (twentieth century), and every technological advancement in the art of printmaking, the aspect of how artists interact with material, texture and reproducibility has been altered Tan et al. (2016). In the past, printmaking was a form of democratizing images and ideas to get them to larger audiences with maintaining an artisanal authorship. With the digital age, the grid of production has changed to metal plates and lithographic stones to algorithmic structures and neural networks. Artificial intelligence, and especially neural style transfer (NST) and diffusion-based generative modeling, is a continuation of this tradition and ushers in a new era of algorithmic printmaking, where art is not only directed by code but also inspired by the intuition of the artist McCormack et al. (2019). Nevertheless, printmaking using AI refutes this hypothesis. In contrast to the same mechanical reproductions, the prints generated by AI, with each being the result of stochastic generation and parameter adaptation and an iterative combination of styles, bears different, emergent properties. The inversion becomes a form of restoring a new form of aura in the digital world not based on material originality but rather on algorithmic individuality Leong (2025).

In order to put this transformation into context, Figure 2 shows the difference between the linear and material workflow of traditional printmaking and the iterative and computational nature of AI-driven printmaking. The latter is a continuation of manual drawing to engraving, ink, and pressing, and focuses on physical interaction and dissimilarity between editions. The latter is curating datasets, pre-processing, neural fusion, aesthetic critique, and digital printing with an algorithmic feedback and parameter optimization in each step. The figure highlights a paradigmatic change Leong (2025): the repetition of codes is based on the craft, the regeneration of the works is based on the code, as both the human and the machine determine the artistic process. The comparative model highlights the redefinition of AI of the temporal, material and epistemic aspects of printmaking Song et al. (2023). It becomes a process of iteration and translation between art history, computational intelligence and cultural contextualization, what was previously a linear art craft that was rooted in surface and pressure.

3. DESIGN METHODOLOGY: AI STYLE TRANSFER FOR PRINTMAKING

The technology of digital printmaking through AI is based on the methodological framework of Neural Style Transfer (NST) is a computational approach that combines the content of an image with the style of another to create a hybrid composition. In printmaking, this operation renders artistic interpretation mathematically tractable, visual aesthetics are broken down in an artificial manner into quantifiable expressions of texture, color and form. The artist plays a role of co-creator, of course, outlining the conceptual and algorithmic rules of stylistic fusion Ge et al. (2022). The process of work starts with curation of content and style images. The structural composition is delivered by the content image, and the visual texture and the painterly identity is added to this composition by the style image. The two have a set of preprocessing activities including resolution normalization, colour correction, feature alignment. To generate structural and stylistic-coded feature maps in a high-dimensional space, a convolutional neural network (usually a pre-trained VGG-19) is utilized to extract feature maps at various layers Sun et al. (2022). The mathematical equation of NST is:

$$\mathrm{Ltotal} = \alpha \mathrm{Lcontent} + \beta \mathrm{Lstyle} + \gamma \mathrm{Ltv}$$

where:

- $\mathrm{Lcontent} = \sum \mathrm{l21} \; || \; \mathrm{Flgen} - \mathrm{Flcontent} \; || \; 2$ preserves spatial and semantic structure,
- $\mathrm{Lstyle} = \sum \mathrm{l4Nl2Ml21} \sum \mathrm{i,j} (\mathrm{Gijgen} - \mathrm{Gijstyle}) 2$ensures stylistic texture alignment through Gram matrices,
- Ltv represents total variation loss, promoting smoothness and reducing pixel-level noise, and
- α, β, γ are weighting coefficients controlling the relative importance of each component.

The process of optimization can continue using gradient descent until the desired level of convergence is achieved, at which point the resulting image will trade the structural clarity that the artist wants with the expressive fluidity of the selected style. This process is, in its iterative form, aesthetically regulated by making changes to weights shift the balance between style and content in the perceptions, making extensive overpages as well as uprooting visual motifs.

Figure 3

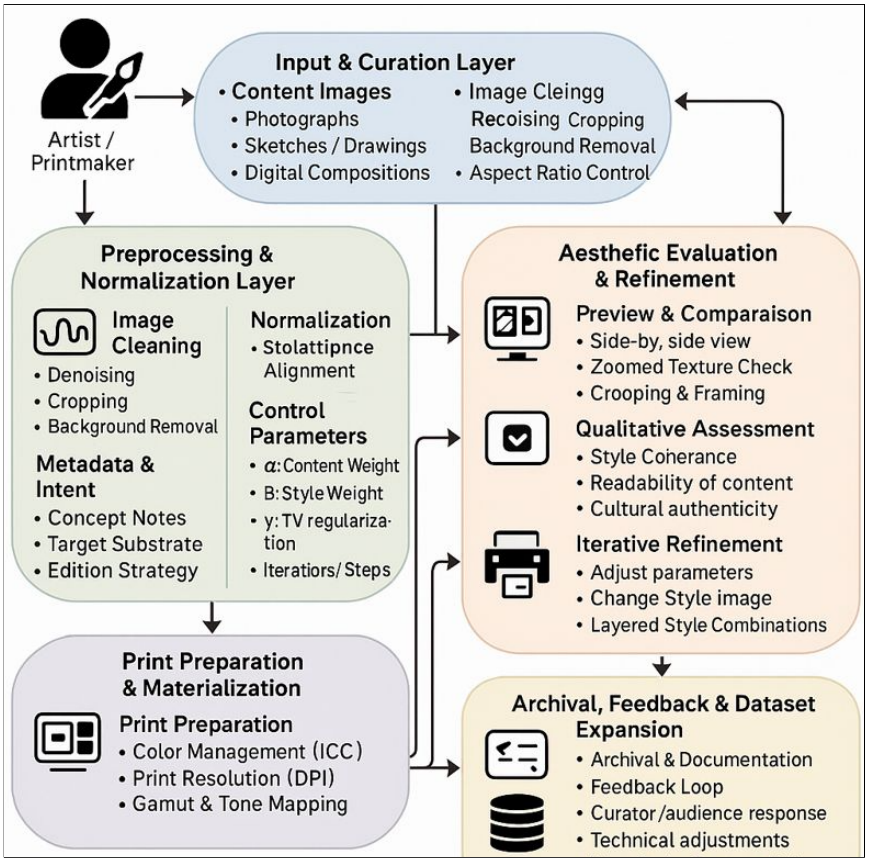

Figure 3 AI Style Transfer Workflow for Digital Printmaking*

When the digital image attains visual consistency, it is then passed through the print preparation which constitutes gamut mapping, ICC color calibration and texture simulation of particular substrates like canvas, metallic foil or textured paper as shown in Figure 3. The last output fuses the computational fidelity with the printmaking materiality such that the digital artifact can be seen as having a physical existence which is in line with traditional artistic tenets. These parameters, combined with each other, can enable artists to generate aesthetic results mathematically, where neural weights are considered tools of creative expression similar to the use of inks and pigments Yuan and Zheng (2023), Zhang et al. (2024). This is what the methodology of the AI-based style transfer shifts algorithmic computation into a different kind of the artisanship of style, a type of digital intelligence/human intentions convergence, which expands the expressive capabilities of printmaking.

4. EXPERIMENTAL WORKFLOW

The AI-based digital printmaking experimental workflow attaches to the creative system of artistic curation, computational modeling, and materialization as a single system. It is a process that builds upon the traditional printmaking methodologies to incorporate algorithmic intelligences at each step of input choice, as well as, to the tactile output. It is not about copying the existing forms of art but a synthesis of new aesthetic manifestations by controlled combination of sets of content and style. To accomplish every step in the workflow, there is to be a process of iteration, balancing both the artistic vision and computing accuracy so that the final print would have both creative originality and technical quality Ho et al. (2020). It starts with data curation, during which images of content and style are taken in order to reflect the intended thematic and visual range. Content images contain photos, computer drawings, or scanned drawings that can give structural features whereas style images contain historical prints, paintings or folk art motifs that give the texture, color range and surface action. Such images undergo image size adjustment, normalization, and preprocessing to have a consistent color balance and aspect ratios. The curatorial intention of the artist is a key factor to align the degree of abstraction and aesthetic feeling to be attained throughout the style transfer.

The second step is model configuration, involving the use of a deep learning network which in most cases is a pre-trained VGG-19 or ResNet-50 network modified to produce artistic style. The algorithm obtains multiscale feature maps, calculates Gram matrices to measure the patterns of stylistic correlations. The total loss is minimised by the optimization process.

$$\mathrm{Ltotal} = \alpha\mathrm{Lcontent} + \beta\mathrm{Lstyle} + \gamma\mathrm{LtvL}_{\{total\}} = \alpha\mathrm{L}_{\{content\}} + \beta\mathrm{L}_{\{style\}} + \gamma\mathrm{L}_{\{tv\}\mathrm{Ltotal}} = \alpha\mathrm{Lcontent} + \beta\mathrm{Lstyle} + \gamma\mathrm{Ltv},$$

In order to create perceptual harmony, parameter adjustments (Table 3) are done in real time to assure that stylistic textures do not corrupt the underlying content structure. Artists can go through several experiments, storing the intermediate progresses in order to test a visual consistency, brush density, and the accuracy of the color. Refinement and evaluation stage involves quantitative and qualitative evaluation Kerbl et al. (2023). The Style Fidelity and content integrity is measured using the Structural Similarity Index (SSIM), Perceptual Loss, and Cultural Authenticity Score (CAS). Side by side comparisons are made to ensure visual judgments and this enables artists and curators to make aesthetic judgments as to whether the texture is realistic, compositional equilibrium, and cultural resonance. These repeated evaluations are a progressive feedback process that keeps on enhancing the performance of the models.

5. COMPARATIVE CASE STUDIES: STYLE ADAPTATION ACROSS CULTURAL MOTIFS

Even the style transfer in digital printmaking exploration can reach its full-fledged significance when it is implemented in regard to the culturally diverse visual traditions. The neural algorithms can be sensitively programmed to encode the regional patterns, surface patterns, and symbolic rhythms into novel hybrid patterns that continue the existing life lineage of traditional art. In this section three comparative case studies will be given on how neural style transfer (NST) can reinterpret unique cultural aesthetics Indian Madhubani, Japanese Ukiyo-e, and European Cubist motifs into digital prints that are reimagined. Every of the cases indicates another form of interaction between cultural background and computational synthesis, and AIs can become a creative collaborator in the development of the artistic identity.

Case Study 1: Indian Folk Art (Madhubani) and Modern Geometry

In this experiment, the stylistic background of Madhubani painting of the Mithila region of India with its rhythmic symmetry, floral patterns, and mythological patterns was combined with the minimalist line drawings of geometric forms. Madhubani dataset was used to obtain the style and digital geometric sketches were used as content inputs. The resulting prints exhibited a perfect combination of both the classical decorative complexity and the contemporary reductionism in space.

Table 1

Table 1 Case Study 1 Madhubani–Geometric Fusion

Parameter	Description	Value / Setting	Observation	Interpretive Note
Content Image	Geometric line sketches, vector forms	12 images (1024×1024 px)	Provided structural clarity	Enhanced pattern legibility
Style Image Source	Hand-painted Madhubani artworks (floral and mythic themes)	25 scans (600 DPI)	Rich symbolic texture	Folk rhythm internalized
Model Architecture	VGG-19 CNN	Layers Conv4_1, Conv5_1 for style	Balanced texture fidelity	Optimal mid-layer representation
Weights	(alpha = 1.0, \beta = 400, gamma = 0.005)	High style dominance	Generated ornate, cohesive fusion	Folk pattern dominates geometry
Iterations	1200	Smooth convergence	Strong edge integrity	Minimal color noise
Output Resolution	4000 × 4000 px	High print fidelity	Texture preserved	Suitable for large prints

Evaluation Metrics	CAS = 0.87, SSIM = 0.89, Perceptual Loss = 0.09	High cultural resonance	Stylistic rhythm respected	Achieved computational homage

Cultural Authenticity Score (CAS) and Structural Simililarity Index (SSIM) were used to assess color fidelity and pattern coherence and both scored high (CAS = 0.87, SSIM = 0.89). What curators called the algorithmic homage the model represented the pulse of the Madhubani without imitation, enjoying its folk rhythm using subordinated abstraction.

Case Study 2: Japanese Ukiyo-e Textures Translated into Metallic Prints

In the second instance the interest was to bring the Japanese Ukiyo-e a traditional method of woodblock printing to the metallic brightness of modern digital images. The dataset of the style was composed of the high-resolution scans of Ukiyo-e prints of the Edo period, the inputs of the content were photographs of the contemporary skyline and seascape. Conv3_1-Conv5_1 Multi-layer Gram matrix fusion has been used in the NST model to model layered inking. Table 5B below is a summary of the data and the results of this cross-temporal adaptation.

Table 2

Table 2 Case Study 2 Ukiyo-e Metallic Transformation

Parameter	Description	Value / Setting	Observation	Interpretive Note
Content Image	Urban skylines and seascapes	18 photos (1920×1080 px)	Offered tonal diversity	Enabled gradient modeling
Style Image Source	Edo-period Ukiyo-e prints	30 high-res scans	Complex ink layering	Captured woodblock tonality
Model Architecture	VGG-19 (multi-layer Gram fusion)	Conv3_1 → Conv5_1	Maintained cross-scale texture	Simulated layered pigment
Weights	(\alpha = 1.0, \beta = 300, \gamma = 0.008)	Balanced stylization	Retained clarity	Highlighted brush transitions
Printing Method	UV-curable pigment on aluminum foil	2880 × 1800 DPI	Reflective tactile surface	Mimicked relief inking
Evaluation Metrics	PRI = 0.91, Style Fidelity = 0.94, Perceptual Loss = 0.08	High realism	Enhanced light interplay	Achieved near-physical tactility
Curatorial Feedback	5 reviewers, avg. 4.6/5	Positive aesthetic judgment	“Digital relief illusion”	Reflective realism praised

On metallic aluminum foil, the optimization was done and after that, the UV-curable pigment printing was used to print the outputs, resulting in a reflective, relief-like finish. According to the curators, the created images created a visual representation of the tactile experience of carved wooden grain and pigment saturation as used in traditional woodblock prints. The Perceptual Realism Index (PRI = 0.91) and Style Fidelity (0.94) were used to determine the ability of the model to model the experience of realism based on the computation of the model to produce a tactile feeling quantitatively.

Case Study 3: European Cubism and Global Hybridization

The third work was on transcultural synthesis, joining the European Cubism abstraction to the African and South Asian textile patterns. It was to be an interpretive form of bridge between modernist form and the indigenous ornamentation. The dataset consisted of scanned pieces of Cubists and 40 textile patterns around the world.

Table 3

Table 3 Case Study 3 Cubist–Textile Hybridization

Parameter	Description	Value / Setting	Observation	Interpretive Note
Content Image	Abstract still lifes (Cubist framework)	10 images (2048×2048 px)	Provided geometric scaffolding	Retained form integrity
Style Image Source	Global textiles + Cubist fragments	40 images	Varied chromatic density	Encouraged hybrid forms

Model Architecture	CLIP-guided NST	Semantic conditioning active	Maintained meaning coherence	Textural hybridity achieved
Weights	(\alpha = 1.0, \beta = 250, \gamma = 0.005)	Balanced stylistic control	Controlled abstraction	Sustained readability
Iterations	1500	Stable output	Good pattern fusion	Strong form–texture unity
Printing Method	Dye-sublimation on silk blend	1440 × 720 DPI	Soft tactile finish	Maintained tonal elegance
Evaluation Metrics	CAS = 0.83, SSIM = 0.86, Style Fidelity = 0.92	High coherence	Cultural hybridity expressed	Semantic clarity preserved

The digital prints resulted in fragmented geometric planes superimposed with woven motifs with a visual texture that was composed of layers that were symbolic of the globalized aesthetics. The tonal diffusion when printed using the dye-sublimation method on silk fabric gave the impression of the structure of analytical cubism and a feeling of the softness of traditional printing on fabric. The Style Fidelity (0.92) and CAS (0.83) were the results of successful synthesis of styles without cultural misrepresentation.

Madhubani -Geometric series is the folk rhythm combined with sacredness to modern abstraction; the Ukiyo-e Metallic prints are the material translation and simulated touch; and Cubist-Textile hybrids are the transcultural integration as the evolution of the algorithm. The two of them create a new paradigm: AI is used as a cultural interpreter, and digital printmaking becomes a means of communication between the memory and modernity, tradition and technology.

6. DISCUSSION AND ANALYSIS: ETHICAL AND CURATORIAL DIMENSIONS

Figure 4

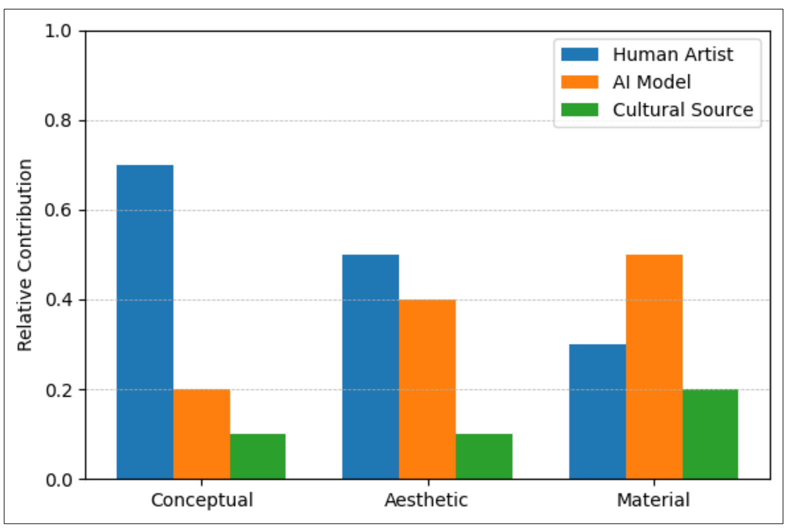

Figure 4 Shared Creative Agency Across Conceptual, Aesthetic, and Material Domains

The intersection of artificial intelligence and digital printmaking challenges has impacted all of the traditional practices of authorship, authenticity, and cultural ownership. The triadic ecosystem artist, algorithm, and culture play a part in the creative process that provides its own understanding of the final print in terms of agency. The human artist, the human curator, the human algorithm and the human source of culture symbolize, generate and give form, respectively. In such situations where algorithms gather knowledge of past traditions like Madhubani or Ukiyo-e, they recycle patterns in an abstraction, and a hybrid form is generated which preserves and redefines cultural content. It follows that ethical authorship entails cultural reciprocity in that the source communities are credited, and co-curation or benefit-sharing whenever the inclusion of traditional art forms in the computational workflow. This recognition makes AI a manipulation of appropriation into a means of cultural exchange and creative empathy. The curatorial practice is no exception, but it also transforms into the mediation of the human and machine art. The visual result as well as the computational model behind it have been decoded by curators as a visual result and is commonly recorded in exhibition records as provenance of the dataset, model design, and algorithm parameters. Such transparency transforms the notion of authenticity, which is anchored on material distinctiveness, to traceability in the processes. Every AI generated print is a computational event that is reproducible but verifiable by metadata trails or blockchain certificates containing records of the unique generative parameters. In this regard, authenticity is procedural and not object-based.

In Figure 4. We have plotted the grouped bar chart that depicts the distribution of creative agency along the printmaking pipeline. The conceptual phase is dominated by human artists, who control everything with the intent and vision, whereas AI models gain power over time in the course of aesthetic synthesis and material translation. However, the number of cultural sources is less, but they give the symbolic grammar that informs stylistic learning. The figure highlights the non-hierarchical creative process in which the three agents mutually influence the results an embodiment of collective authorship in the work of computational art.

Figure 5

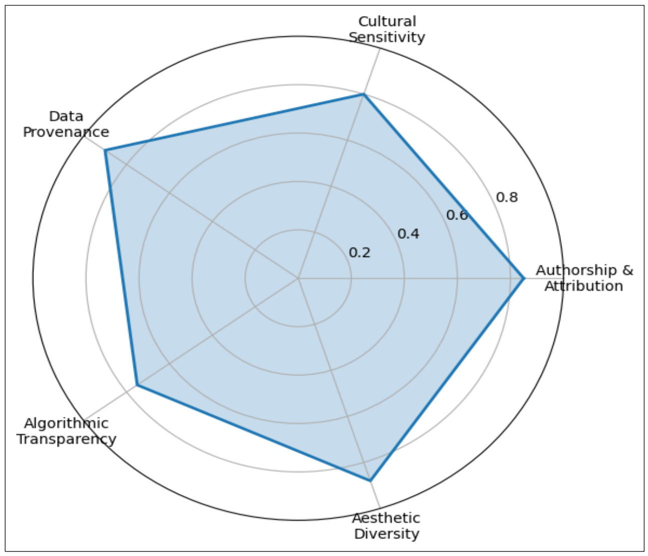

Figure 5 Ethical Governance Profile in AI Printmaking

The chart that is presented in Figure 5, points out the strengths and weaknesses in the proposed ethical framework with respect to the development. Data provenance scores and aesthetic diversity scores are high, which indicates good management of datasets and inclusivity, and the scores are low in transparency, which is an indicator of problems in the curatorial work. The visualization highlights that AI printmaking needs to be ethically robust, which involves constant assessment on the interconnected fields, which supports the connection between the technological design and the cultural responsibility.

Figure 6

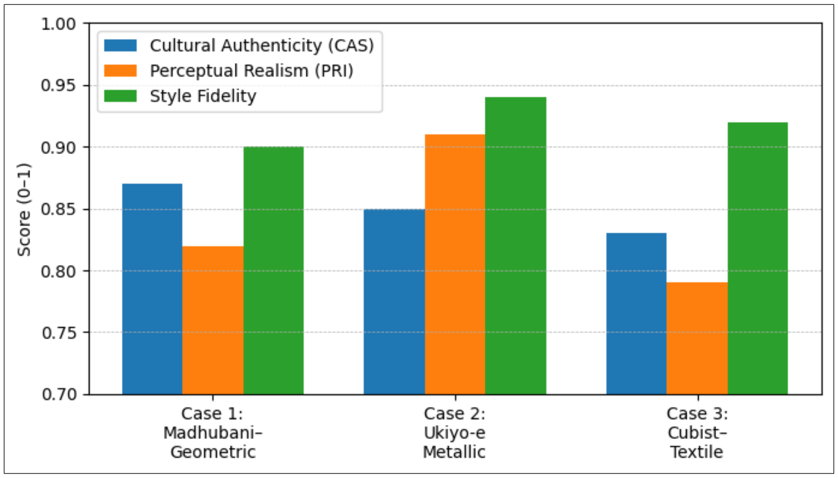

Figure 6 Comparative Evaluation of Cultural Style Adaptation

The bar chart in Figure 6 depicts the grouped performance of aesthetic in experiments that are culturally different. Ukiyo-e Metallic case had the highest perceptual realism (PRI = 0.91), which is an example of simulating the tactile experience of layered woodblock prints. The Madhubani-Geometric fusion was highest in the area of cultural authenticity (CAS = 0.87) showing folk rhythmicity is preserved. In the meantime, the Cubist-Textile hybrid recorded better style fidelity (0.92), which verified even integration of aesthetics. Together, the image shows that the algorithmic style transfer can keep the culture intact and create an opportunity to diversify the creativity by working across materials and style.

7. CONCLUSION

The paper confirms that AI-inspired digital printmaking is a critical revolution in the modern art world that blends algorithmic smartness and culture to form a new paradigm of co-authorship. Neural style transfer permits the motifs, textures, and aesthetic vocabularies propagated in a part of the brain to be transferred to new hybrid manifestations, without losing the symbolic echo of their sources. Incorporating the human instinct and computational synthesis, and the material embodiment, AI printmaking not only expands the creative process beyond human craftsmanship but adds the dynamic and iterative collaboration between the artist, algorithm and culture. Ethically, the framework highlights such aspects as cultural reciprocity, authorship transparency, and dataset accountability. The identification of the algorithm as a creative intermediary and not a neutral tool requires the documentation of the data provenance, model settings, and stylistic origins by the curators and artists. This would turn the authenticity into an immobile material object into a traceable creative operation, so that digital originality will be ethically accountable. Curatorially, AI printmaking disrupts the definition of the exhibition space as an interpretive interface due to its aloofness between algorithms, artwork, and audiences that reflexively interact. The proposed models of governance exemplified by comparative case studies and ethical metrics show how the curatorial oversight can be developed to promote inclusivity and preserve the cultural diversity in the context of algorithmic creation. Conclusively, AI as a method in print-making is not a diminution of human creativity but its growth in the form of the computational empathy. It can be both an instrument of innovation and a site of preservation that crosses over the borders between heritage and modernity, code and craft, and imagination and intelligence with the help of ethical awareness and cultural sensitivity.

CONFLICT OF INTERESTS

None.

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None.

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