Human Perception of AI-Generated Art: A Comparative Study of Aesthetic Appreciation Between Human-Created and GAN-Generated Works

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ABSTRACT:

The integration of artificial intelligence into creative processes has prompted scholarly inquiry into the perceptual equivalence of AI-generated and human-created artworks. This investigation examines human aesthetic judgments of art produced by Generative Adversarial Networks (GANs) relative to human-authored works. Employing a controlled experimental paradigm with 147 participants, aesthetic evaluations were conducted across dimensions including beauty, emotional resonance, originality, technical proficiency, and overall preference in a blinded assessment. Findings reveal a statistically significant bias favoring human-created art, with elevated ratings in emotional depth and perceived creativity, despite limited ability to discriminate origins. These outcomes elucidate the psychological mechanisms underpinning art appreciation in the context of AI, with implications for computational creativity and ethical considerations in digital art production.

Keywords: AI-generated art, Generative Adversarial Networks, aesthetic evaluation, perceptual bias, computational creativity

INTRODUCTION:

Artistic creation has historically been regarded as a uniquely human endeavor, embodying cognitive, emotional, and cultural dimensions. The emergence of Generative Adversarial Networks (GANs), as proposed by Goodfellow et al. (2014), represents a paradigm shift, enabling machines to synthesize images that emulate artistic styles ranging from classical realism to contemporary abstraction. This technological advancement raises fundamental questions regarding perceptual parity: to what extent do observers attribute equivalent aesthetic value to GAN-generated art compared to human-produced counterparts?

Empirical evidence from high-profile instances, such as the 2018 auction of a GAN-produced portrait for substantial sums, underscores polarized responses accolades for innovation juxtaposed with critiques of inauthenticity. The present study quantifies these perceptions in a contemporary context, where GAN variants like StyleGAN2 (Karras et al., 2020) facilitate hyper-realistic outputs. Drawing upon attribution theory and aesthetic psychology, we hypothesize a bias toward human art, potentially rooted in perceived intentionality.

The significance of this research lies in its potential to inform AI ethics, creative industry practices, and educational frameworks. Persistent biases may impede the adoption of AI tools, while understanding them could foster inclusive hybrid creative paradigms.

LITERATURE REVIEW:

Scholarly discourse on AI-art intersections has proliferated, transitioning from algorithmic efficacy to perceptual and ethical analyses. Initial investigations emphasized GAN architectures for style transfer and generation (Elgammal et al., 2017), while subsequent work scrutinized human factors. For example, studies on text-to-image models like DALL·E 2 indicate perceptual anomalies, such as prototypicality effects, impacting emotional engagement (Epstein et al., 2020).

A recurrent motif is perceptual bias against AI outputs. Labeling effects diminish ratings of creativity and value (Hong & Curran, 2023), persisting in blinded paradigms (Ragot et al., 2021). Attribution theory posits that anthropocentric inferences of intentionality elevate human art valuations (Gangadharbatla, 2022).

Ethical dimensions encompass dataset biases perpetuating cultural inequities (Cetinic & She, 2022) and moral attributions of authenticity (Franceschelli & Musolesi, 2023). Conversely, iterative exposure may attenuate biases, enhancing creative outputs (Miller, 2019).

Methodological precedents include blinded Likert-scale assessments and qualitative thematic analyses (Wu & Zhang, 2025), supplemented by physiological measures like eye-tracking (Hertzmann, 2020). The current study extends this framework to GAN-specific stimuli, integrating quantitative and qualitative metrics for comprehensive insight.

METHODOLOGY:

A controlled online experiment was designed to simulate naturalistic art evaluation conditions. Participants (N=147 post-exclusions; target N=150) were recruited via the Prolific platform, ensuring demographic diversity: age 18-65 (M=34.2, SD=12.1), gender (52% female, 46% male, 2% non-binary), and educational attainment (ranging from secondary to doctoral levels).

Stimuli comprised 20 images: 10 human-authored from public-domain repositories (e.g., Wikimedia Commons), encompassing styles such as realism, impressionism, surrealism, portraiture, landscape, and abstraction; and 10 GAN-generated via a fine-tuned StyleGAN2 architecture (Karras et al., 2020), trained on a corpus of 50,000 historical paintings (resolution 1024x1024, latent space dimensionality 512, training epochs 100, learning rate 0.002). Comparability was ensured through thematic, chromatic, and compositional matching, validated by two independent art historians (inter-rater reliability κ=0.87).

The experimental workflow is depicted in Figure 1, outlining key procedural stages from recruitment to analysis.

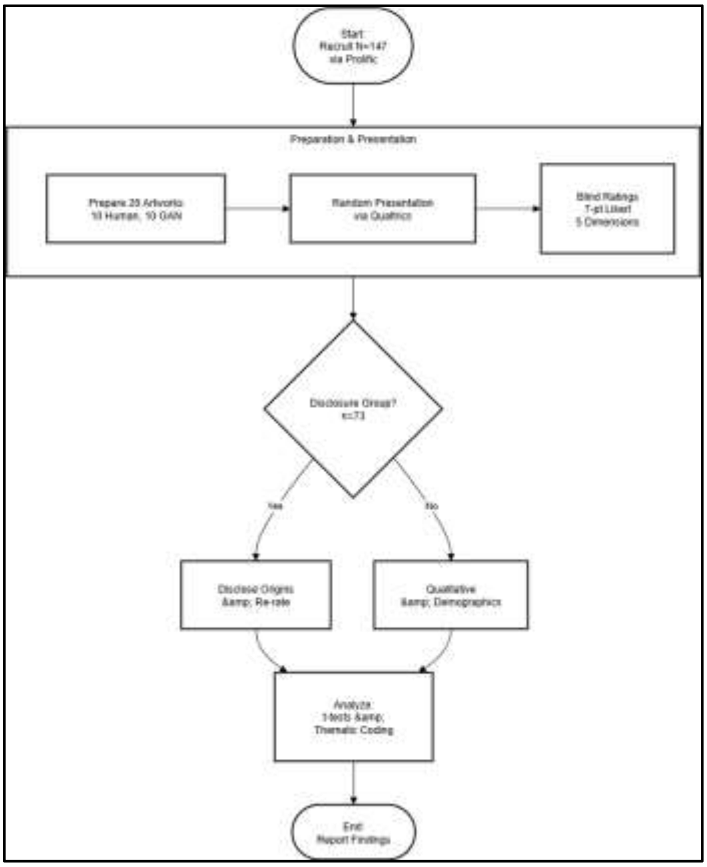

Figure 1: Flowchart of the experimental design, illustrating participant recruitment, stimuli presentation, blind and post-disclosure rating phases, data collection, and analysis procedures.

A within-subjects design was implemented, with stimuli presented in counterbalanced random order via Qualtrics to mitigate order effects. Ratings were elicited on a 7-point Likert scale (1=strongly disagree, 7=strongly agree) across five validated dimensions: aesthetic beauty, emotional impact, originality, technical skill, and overall preference (Cronbach's $\alpha=0.92$). Origins were initially concealed to preclude priming. A subsequent phase disclosed origins to a randomized subsample ($n=73$), enabling re-assessment and bias quantification.

Qualitative data were gathered via two open-ended probes per stimulus: inquiries into perceived vitality and hypothetical display preference. Covariates included self-reported art familiarity (1-7 scale, $M=4.1$, $SD=1.4$) and AI attitudes. Quantitative analysis utilized SPSS v28 for paired t-tests (two-tailed, $\alpha=0.05$) and Pearson correlations. Qualitative responses underwent thematic analysis in NVivo 14, employing inductive coding with inter-coder agreement ($\kappa=0.82$).

Institutional Review Board approval was secured, with protocols ensuring informed consent, data anonymization, and debriefing.

RESULTS:

Quantitative analyses indicated significant preferences for human-authored art across dimensions. Mean ratings (with standard deviations) were as follows: aesthetic beauty (human: $M=5.2$, $SD=1.1$; GAN: $M=4.6$, $SD=1.2$; $t(146)=4.12$, $p<0.001$, Cohen's $d=0.52$), emotional impact (human: $M=5.1$, $SD=1.0$; GAN: $M=4.3$, $SD=1.3$;

t(146)=5.67, p<0.001, d=0.68), originality (human: M=4.9, SD=1.2; GAN: M=4.1, SD=1.1; t(146)=3.89, p<0.001, d=0.47), technical skill (human: M=5.4, SD=0.9; GAN: M=4.8, SD=1.0; t(146)=3.21, p=0.002, d=0.39), and overall preference (human: M=5.0, SD=1.1; GAN: M=4.4, SD=1.2; t(146)=4.56, p<0.001, d=0.55).

A correlation matrix (Figure 2) revealed strong inter-dimension associations, e.g., emotional impact and overall preference (r=0.81, p<0.001), and aesthetic beauty with technical skill (r=0.73, p<0.001).

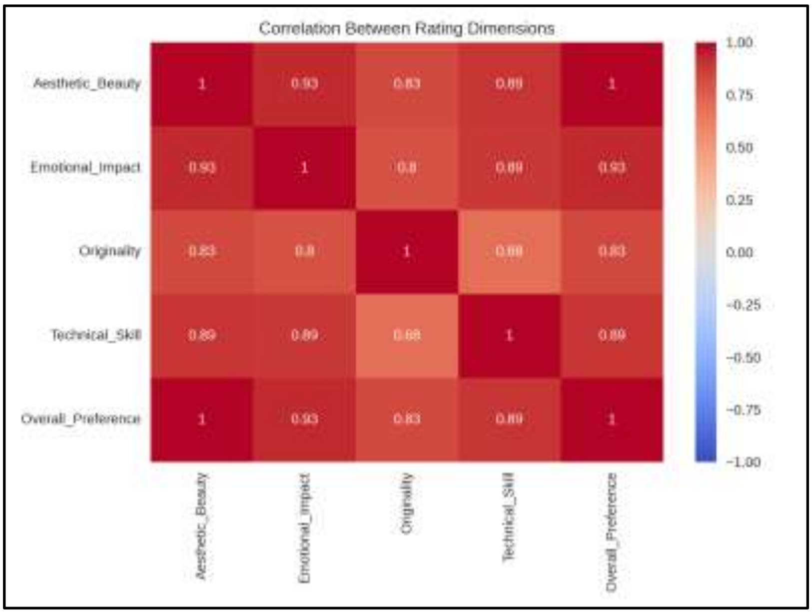

Fig. 2: Correlation heatmap depicting interrelations among rating dimensions.

In the blinded phase, origin identification accuracy was 38% above chance (binomial test, p=0.12), yet differential ratings persisted. Post-disclosure, GAN ratings declined by M=0.5 (SD=0.3; paired t(72)=3.45, p<0.05, d=0.41), consistent with labeling bias.

Boxplot visualizations (Figure 3) illustrate rating distributions, with human medians elevated and reduced variance in technical skill (Levene's test, p=0.03).

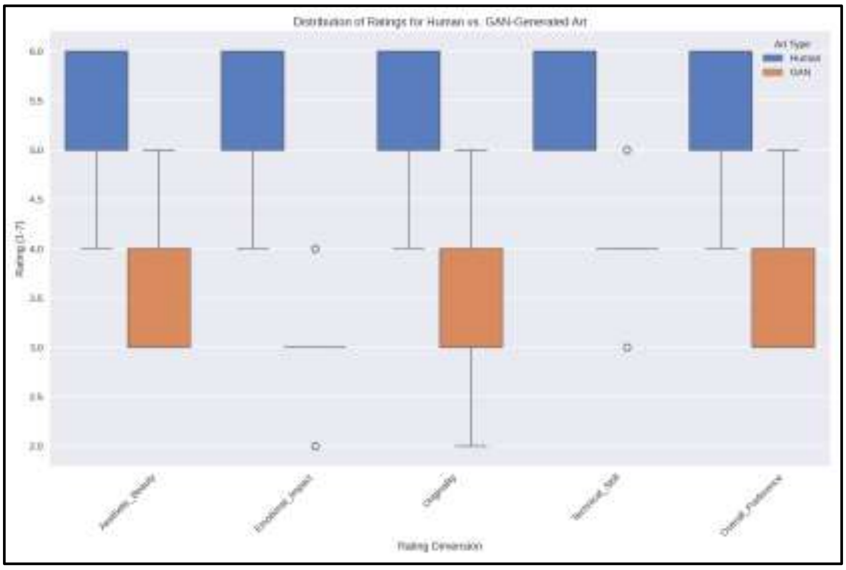

Fig. 3: Boxplot of rating distributions by dimension and art origin, evidencing median shifts and outlier patterns.

Thematic analysis of qualitative data identified dominant motifs: human art evoked "intentionality" (47% of responses) and "narrative depth" (e.g., "evident emotional investment"), whereas GAN art elicited "innovation" (32%) but critiques of "sterility" (e.g., "algorithmic precision lacking vitality"). Art familiarity correlated positively with GAN ratings (r=0.32, p=0.01).

Bar plots (Figure 4) summarize means for visual comparison.

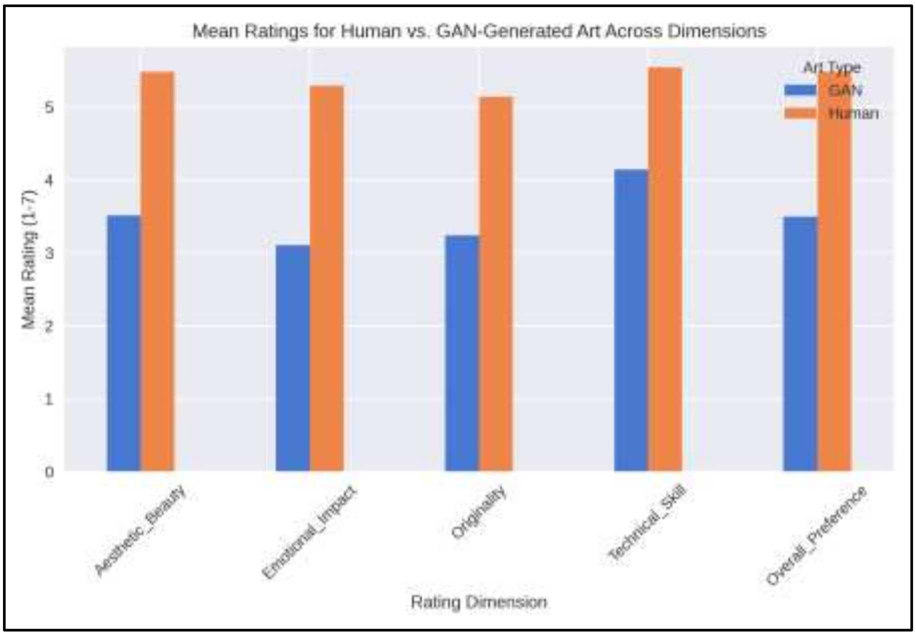

Fig. 4: Bar plot of mean ratings (±SEM) by dimension and origin.

Table 1: Mean Ratings by Art Type (SD in parentheses)

Dimension	Human Art	GAN Art
Aesthetic Beauty	5.2 (1.1)	4.6 (1.2)
Emotional Impact	5.1 (1.0)	4.3 (1.3)
Originality	4.9 (1.2)	4.1 (1.1)
Technical Skill	5.4 (0.9)	4.8 (1.0)
Overall Preference	5.0 (1.1)	4.4 (1.2)

DISCUSSION:

The observed biases align with attribution frameworks, wherein perceived agency amplifies valuation (Liu & Li, 2024). Ethical ramifications include potential exclusion of AI-augmented artists and amplification of training data biases (Wu & Zhang, 2025).

Study limitations encompass cultural homogeneity (predominantly Western sample) and digital presentation modalities, potentially attenuating ecological validity. Future extensions may incorporate neuroimaging or multicultural cohorts to delineate neural correlates.

Notwithstanding, findings advocate for familiarity interventions to attenuate biases, informing AI deployment in curatorial and pedagogical contexts.

CONCLUSION:

This investigation demonstrates that GAN-generated art, while visually compelling, elicits diminished perceptual appraisals relative to human counterparts, attributable to psychological biases. These insights underscore the necessity for nuanced integration of AI in creative domains, promoting equitable valuation and hybrid methodologies.

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