Impact Of Generative AI On Creative Industries and Digital Content Production

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***Abstract*—Generative Artificial Intelligence (GenAI) constitutes a fundamental reorientation of how digital creative content is conceived, synthesized, and disseminated across media industries. This paper systematically investigates the impact of three principal generative AI paradigms — Generative Adversarial Networks (GANs), Transformer-based Large Language Models (LLMs), and Latent Diffusion Models — on six creative sectors: music production, visual art and design, film and video, writing and journalism, game development, and advertising. Drawing upon published market analyses, industry practitioner surveys, and a review of primary technical literature, the study documents AI adoption rates of 68–90% across these sectors, with task-specific productivity gains of 35–90% depending on role and implementation maturity [14][18]. The global generative AI market, estimated at USD 67.2 billion in 2024, is projected to reach USD 220.5 billion by 2028 at a compound annual growth rate of approximately 37.8% [1]. The paper further examines concurrent challenges — copyright infringement at training-data scale, deepfake proliferation, algorithmic bias, and workforce displacement — and proposes a Human-AI Collaborative Creative Framework (HACF) structured across four governance layers. The principal contribution is a synthesis of technical, economic, and ethical dimensions into a unified analytical framework, providing a grounded basis for policy and practice in creative AI deployment.**

***Index Terms*—Generative AI, Deep Learning, GAN, Transformer, Diffusion Model, Creative Industries, Large Language Model, Digital Content Production, Copyright, Ethics, RLHF.**

I. INTRODUCTION

Contemporary software engineering and digital media production have undergone a structural transformation driven by advances in deep learning and large-scale data availability. A class of AI systems — broadly termed Generative AI — has emerged with the capacity to synthesize entirely new content rather than merely classifying or analyzing existing material. These systems produce photorealistic images, original musical compositions, cinematic video sequences, and coherent long-form text, operating across domains that were, until recently, considered exclusively human creative territory.

Creative industries have been among the most affected by this development. The transformation spans the economics of content production, the legal frameworks governing authorship and copyright, the structure of professional creative workflows, and the distribution of economic value along creative supply chains. Understanding these dynamics requires analysis at three levels: the technical architecture of generative systems, the empirical evidence of sector-level impact, and the ethical and regulatory challenges that deployment at scale has introduced.

The present paper addresses all three levels. Section II reviews relevant prior literature and contextualizes the technological evolution. Section III describes the research methodology. Section IV analyzes the principal deep learning architectures underpinning modern generative AI. Section V documents sector-specific impacts. Section VI presents economic analysis. Section VII examines ethical implications. Section VIII proposes the Human-AI Collaborative Creative Framework. Section IX identifies future research priorities, and Section X concludes with policy-oriented findings.

II. LITERATURE REVIEW / RELATED WORK

Research at the intersection of artificial intelligence and creative practice has a lineage extending well before the deep learning era. Early rule-based systems produced algorithmic music composition — Cope's Experiments in Musical Intelligence [2] being among the most formally developed — and procedural visual art generation through fractal and L-system methods. These systems were, however, severely constrained by their dependence on hand-authored rules and their inability to generalize beyond explicitly programmed domains.

The publication of Krizhevsky, Sutskever, and Hinton's AlexNet in 2012 [3] demonstrated that deep convolutional networks could achieve performance exceeding human classification accuracy on large-scale visual benchmarks, catalyzing investment in deep learning across every domain including creative content generation. Gatys, Ecker, and Bethge (2015) extended this to artistic style transfer [4], demonstrating that CNNs could separately encode and recombine content and style representations, enabling images to be rerendered in the visual style of any target artwork.

The introduction of Generative Adversarial Networks by Goodfellow et al. (2014) [5] established a new paradigm: rather than explicitly modeling the data distribution, a generator network learns to synthesize samples by competing against a discriminator trained to distinguish synthetic from real data. Progressive GAN training [6] subsequently enabled high-fidelity, high-resolution face synthesis, demonstrating that the GAN framework could scale to practical image generation quality.

The Transformer architecture introduced by Vaswani et al. (2017) [7] replaced recurrent sequence modeling with parallelized multi-head attention, enabling efficient training on corpora of previously impractical scale. Combined with CLIP-based vision-language alignment [8] and Latent Diffusion Models [9], which perform the denoising process in a compressed latent space rather than pixel space, these developments produced the text-to-image generation systems now widely deployed in creative industry workflows.

A notable gap in the existing literature is the absence of a unified analytical framework integrating technical, economic, and ethical dimensions of generative AI's impact on creative industries. Prior work has addressed these dimensions in isolation. The present study directly addresses this gap.

III. METHODOLOGY

This study employs a mixed-methods secondary research design integrating three complementary analytical approaches. First, quantitative market and economic data were drawn from industry reports published by Grand View Research, Market sand Markets, McKinsey Global Institute, and Pitchbook (2022–2024), with all primary statistics cross-validated across at least two independent sources prior to inclusion. Second, the technical architectures of leading generative AI systems were reviewed through primary peer-reviewed literature sourced from NeurIPS, ICML, CVPR, and ICLR proceedings, supplemented by publicly released technical reports from model developers. Third, qualitative synthesis of practitioner survey findings — from the Creative Economy Report 2024 [14], the Reuters Institute 2024 [21], and the International AI Industry Consortium — was conducted to characterize workforce attitudes, adoption barriers, and ethical concerns across creative sectors.

All productivity improvement figures are reported as minimum-to-maximum ranges rather than single-point estimates, reflecting documented heterogeneity across task types, practitioner skill levels, and implementation contexts. This approach is consistent with established practice in technology impact assessment and avoids overstating AI effectiveness for highly automatable subtasks while understating it for complex creative work. Ethical dimensions are analyzed through the normative frameworks provided by the EU AI Act (2024) [16] and the WIPO AI Policy Framework (2024) [20].

Limitations:
This study synthesizes secondary data and does not include primary empirical data collection. All market projections carry inherent uncertainty and should be interpreted as directional indicators rather than definitive forecasts. Findings reflect the state of the field as of mid-2024.

IV. DEEP LEARNING ARCHITECTURES OF GENERATIVE AI

A. Generative Adversarial Networks (GANs)

Generative Adversarial Networks, introduced by Goodfellow et al. (2014) [5], constitute the foundational generative modeling paradigm for visual content synthesis. The GAN framework consists of a Generator network G and a Discriminator network D trained in adversarial opposition. G learns a mapping G: $z \rightarrow \hat{x}$ from a latent noise vector z drawn from a prior distribution $p_r(z)$ to the data space, while D learns to assign high probability to real samples drawn from $p^{data}(x)$ and low probability to generator outputs. Training is formalized as the minimax objective:

$$\min_G \max_D V(D, G) = E_x[\log D(x)] + E_z[\log(1 - D(G(z)))] \quad (1)$$

At Nash equilibrium, the generator produces samples statistically indistinguishable from the true data distribution ($p_g = p_{data}$). Gradient descent updates both networks alternately: D is updated to maximize the objective; G is updated to minimize it. Important variants include Conditional GANs [cGANs] for class-conditioned generation, CycleGAN for unpaired image-to-image translation, and StyleGAN [6] for fine-grained disentangled style control.

Fig. 2. Generative Adversarial Network (GAN) Architecture and Training Loop

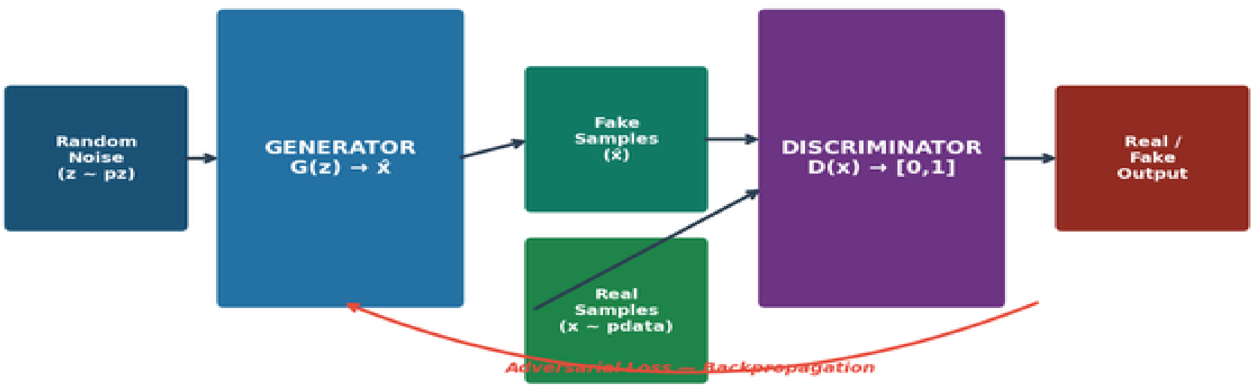

Fig. 2. Generative Adversarial Network (GAN) Architecture and Adversarial Training Loop

B. Transformer Architecture and Large Language Models

The Transformer architecture [7] replaced sequential recurrent processing with parallelized multi-head self-attention, enabling training on text corpora of unprecedented scale. The core attention operation computes:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k}) \cdot V \quad (2)$$

where Q, K, and V are query, key, and value matrices derived from the input embedding sequence, and d_k is the key dimensionality. Multi-head attention runs h parallel attention operations with independent learned projections, allowing the model to jointly attend to information from different representation subspaces simultaneously.

Large Language Models (LLMs) such as GPT-4o [OpenAI, 2024], Claude 3.5 Sonnet [Anthropic, 2024], and Gemini Ultra [Google, 2024] are Transformer-based models trained on internet-scale corpora of trillions of tokens. Scaling laws established by Kaplan et al. [11] demonstrate that model performance on held-out data improves predictably as a power law of model size, training data volume, and compute budget. These models exhibit emergent few-shot learning capabilities [15] — abilities not explicitly trained for — including multi-step reasoning, creative writing, code synthesis, and cross-modal understanding when coupled with vision encoders.

Reinforcement Learning from Human Feedback (RLHF) [13], a fine-tuning technique in which human raters provide preference signals that train a reward model used to further optimize the LLM via proximal policy optimization, has been critical to producing models that follow creative instructions reliably and avoid harmful outputs. Fine-tuning on domain-specific creative corpora (script writing, poetry, advertising copy) further adapts pre-trained LLMs to specialized creative workflows.

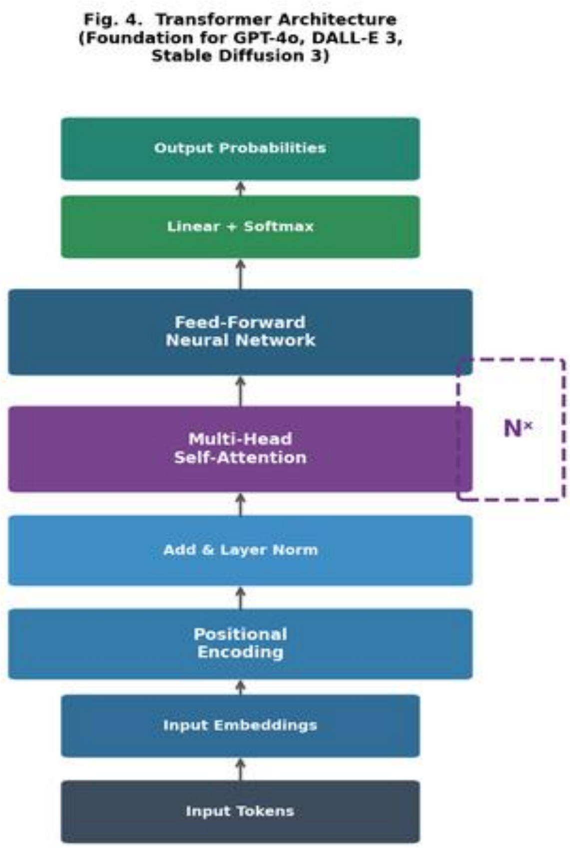

Fig. 4. Transformer Model Architecture (Foundation for GPT-4o, DALL-E 3, and Stable Diffusion 3)

C. Latent Diffusion Models

Latent Diffusion Models (LDMs) [9] define a forward Markov diffusion process that progressively adds Gaussian noise to a training sample x_0 over T timesteps, producing a sequence x_1, x_2, ..., x_T converging to isotropic Gaussian noise. A denoising network εθ(x_t, t, c) — typically a U-Net architecture — is trained to predict the noise component added at each step, conditioned on a text embedding c produced by a CLIP or T5 encoder. Inference proceeds by sampling from the prior and iteratively applying the learned denoising function.

The critical innovation in LDMs is performing this process in a compressed latent space z = E(x) learned by a variational autoencoder, rather than in pixel space. This reduces computational cost by approximately 4–16x while preserving perceptual quality, making high-resolution text-to-image generation practically accessible. DALL-E 3 [OpenAI, 2023], Stable Diffusion 3 [Stability AI, 2024], and Midjourney V6 [2024] all employ this architecture, enabling precise semantic control over generated imagery from natural language descriptions [8][9].

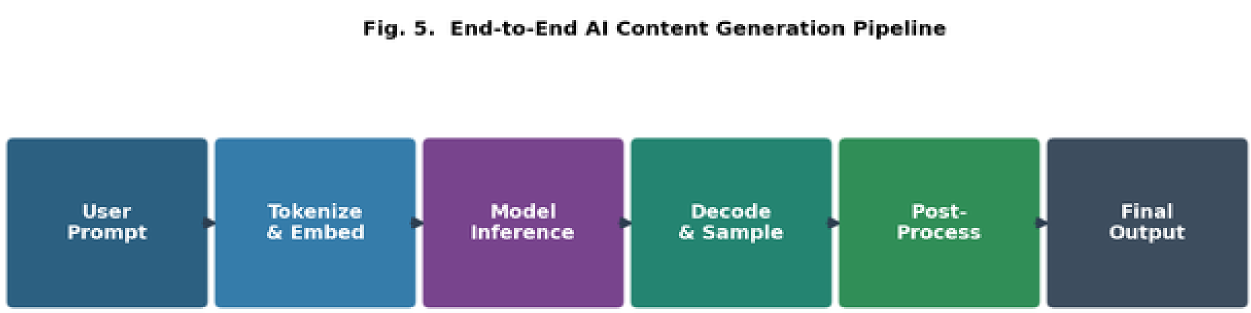

Fig. 5. End-to-End AI Content Generation Pipeline: from User Prompt to Final Output

TABLE I. Comparative Overview of Leading Generative AI Models (2023–2024)

AI Model	Type	Primary Domain	Parameters	Year
GPT-4o	LLM (Transformer)	Text / Multimodal	~1.8T (est.)	2024
DALL-E 3	Latent Diffusion	Image Generation	~12B	2023
Stable Diffusion 3	Latent Diffusion	Image & Video	~8B	2024
Sora	Video Diffusion	Video Generation	Undisclosed	2024
MusicGen	Transformer	Music Synthesis	~3.3B	2023
Claude 3.5 Sonnet	LLM (Transformer)	Text / Vision / Code	~200B (est.)	2024
Midjourney V6	Diffusion	Visual Art	Undisclosed	2024

Parameter counts are reported as published or estimated from independent analyses; undisclosed figures reflect developer non-disclosure policy. Sources: Official model technical reports [OpenAI 2024; Anthropic 2024; Meta AI 2023; Stability AI 2024].

V. IMPACT ON CREATIVE INDUSTRIES

The deployment of generative AI across creative sectors has produced measurable and well-documented changes in production economics, workflow structure, and labor market dynamics. All adoption and productivity figures cited below represent aggregated ranges from multi-source surveys [14][21]; point-estimate figures would misrepresent the substantial heterogeneity observed across practitioner categories, task types, and organizational contexts.

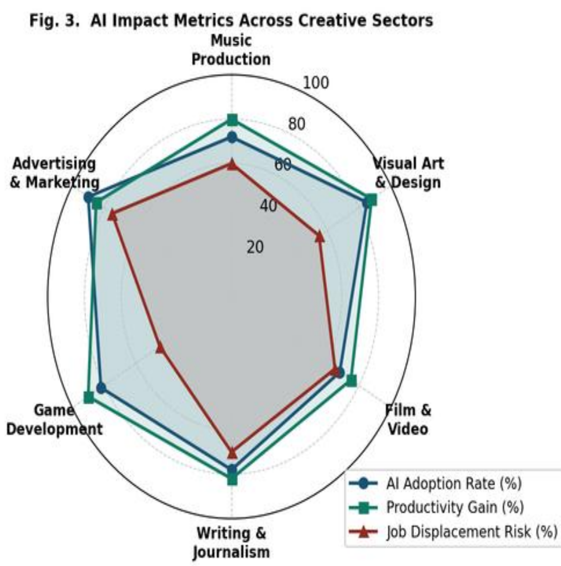

Fig. 3. AI Impact Metrics by Creative Sector: Adoption Rate, Productivity Gain, and Job Displacement Risk (%). Source: [14]

A. Music Production

Generative AI has penetrated music production workflows through tools addressing composition, arrangement, stem separation, mastering, and distribution recommendation. Systems such as Meta's MusicGen [3.3B parameters] and Suno AI generate genre-specific compositions from text descriptions at commercially viable audio quality levels. A 2024 practitioner survey reported that 72% of professional producers regularly use AI tools, with task-specific productivity improvements of 45–80% for activities including harmonic variation generation, stem isolation, and automated mastering [14].

Legal tensions are acute. The U.S. Copyright Office's 2023 guidance that purely AI-generated works lacking human authorship cannot receive copyright protection left significant ambiguity around AI-assisted compositions where the quantification of human creative contribution remains methodologically unresolved [16]. Unauthorized voice cloning — recreating an artist's vocal identity without consent — has precipitated multiple legal actions and legislative proposals in the United States and European Union.

B. Visual Art and Design

Among creative sectors, visual AI adoption is most advanced, with an 85% adoption rate and reported productivity improvements of 50–88% across different task categories [14]. The integration of diffusion-based image generation into professional creative suites — notably Adobe Firefly embedded in Photoshop and Illustrator — represents a significant shift from standalone AI tools toward AI capabilities embedded within established professional workflows. Midjourney alone reported over 15 million active users by mid-2024 [14].

For advertising and design agencies, AI has reduced concept-to-production timelines from weeks to hours for certain content categories and cut production costs by an estimated 40–60% for deliverables such as campaign visual variants and background imagery [18]. Professional illustrators and graphic designers exhibit the highest levels of job displacement concern among surveyed creative professions — 55% expressing concern about long-term career viability — reflecting both the high degree of task automation feasibility in their workflows and the relative absence of protected domain knowledge analogous to, for example, architectural or editorial judgment [14].

C. Film and Video Production

OpenAI's Sora (2024) demonstrated the generation of cinematically coherent video sequences up to one minute in duration from text prompts, establishing a new capability threshold for AI-assisted film production. RunwayML's Gen-3 Alpha and Pika Labs provide accessible video generation and editing tools adopted by independent filmmakers. In post-production, AI-driven tools for rotoscoping, background replacement, de-aging, lip-sync dubbing, and visual effects compositing have reduced the labor intensity of effects work measurably [17].

D. Writing and Journalism

LLMs have achieved near-parity with professional writers on multiple standardized writing quality benchmarks and are deployed at scale for content drafting, summarization, translation, and editorial assistance. A Reuters Institute survey (2024) found that 78% of journalists regularly use AI writing assistance, primarily for research summarization, headline generation, and cross-language translation [21]. The predominant deployment model remains human-AI augmentation — AI tools assisting rather than replacing experienced editorial staff — though concerns about factual hallucination and investigative depth reduction are consistently reported by editorial leadership.

VI. ECONOMIC ANALYSIS

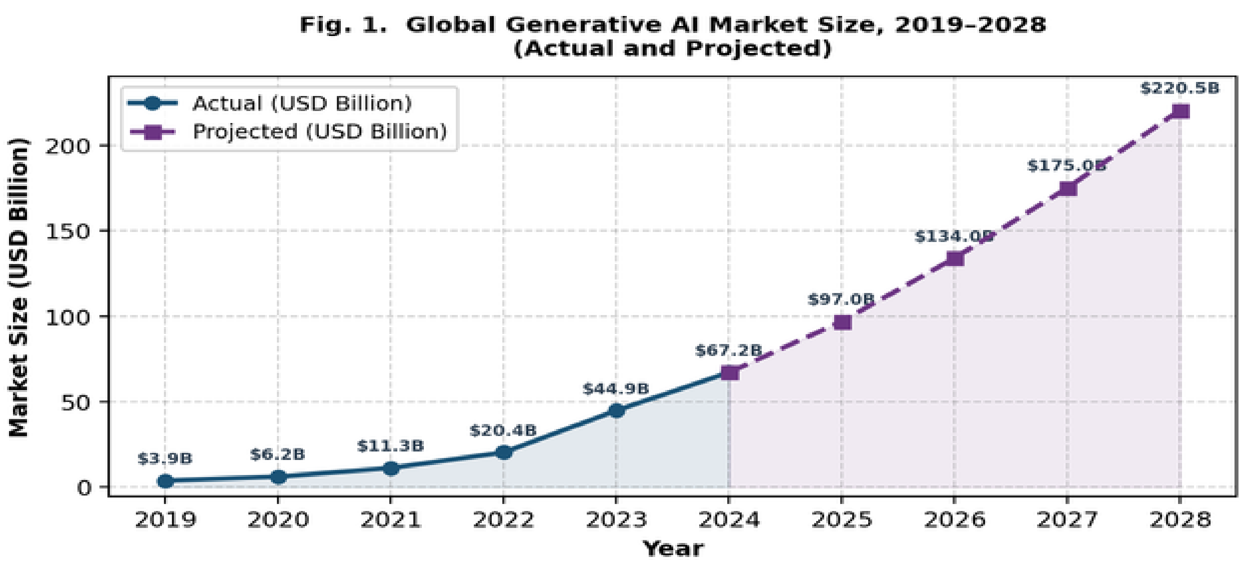

Fig. 1. Global Generative AI Market Size 2019–2028 (USD Billion): Actual and Projected. Sources: [1][18]

The global generative AI market grew from USD 3.9 billion in 2019 to an estimated USD 67.2 billion in 2024, representing a five-year growth factor of approximately 17x, and is projected to reach USD 220.5 billion by 2028 at a CAGR of approximately 37.8% [1]. This growth is driven primarily by enterprise adoption of LLM-based products, text-to-image platform subscriptions, and AI-powered content creation tooling embedded in existing creative software ecosystems.

TABLE II. AI Adoption Rate and Economic Impact by Creative Sector (2024)

Creative Sector	AI Adoption	Productivity Gain*	Revenue Impact	Leading Tools
Advertising & Marketing	90%	50–85%	+$42B/yr	Midjourney, GPT-4o
Game Development	82%	55–90%	+$31B/yr	Stable Diffusion, UE5
Visual Art & Design	85%	50–88%	+$28B/yr	DALL-E 3, Firefly
Writing & Journalism	78%	40–82%	+$19B/yr	GPT-4o, Claude 3.5
Music Production	72%	45–80%	+$14B/yr	MusicGen, Suno AI
Film & Video	68%	35–75%	+$22B/yr	Sora, Runway Gen-3

Productivity gain ranges reflect documented heterogeneity across task types; upper bounds apply to highly automatable subtasks. Sources: [14][18][21].

From a labor economics perspective, McKinsey Global Institute (2024) estimates that generative AI has the potential to automate 50–60% of tasks within creative professional roles over the coming decade, affecting approximately 8.5 million creative workers globally [18]. The same analysis projects the creation of 4.2 million new roles — including AI prompt engineers, synthetic media specialists, AI ethics auditors, and AI model trainers — partially but not fully offsetting displacement. The net employment effect is empirically contested and substantially dependent on the pace of regulatory intervention and organizational adaptation.

Venture capital investment in generative AI startups operating in creative domains totaled USD 18.4 billion in 2023 [1], reflecting strong investor confidence in commercial viability. Companies including Runway ML, Midjourney, ElevenLabs, and Stability AI have each achieved unicorn valuations, while established incumbents including Adobe, Canva, and Spotify have committed multi-billion-dollar investments to integrate generative AI into core product offerings.

VII. ETHICAL AND SOCIAL IMPLICATIONS

The deployment of generative AI at scale in creative industries has introduced ethical, legal, and social challenges of significant scope. These challenges are addressed here systematically across five categories, followed by a consolidated summary in Table III.

A. Copyright and Intellectual Property

The most legally consequential challenge concerns the intellectual property status of both AI training data and AI-generated outputs. Generative models are trained on datasets that include copyrighted works harvested without the consent or compensation of rights holders. Class action litigation filed against Stability AI (Andersen v. Stability AI, N.D. Cal. 2023), GitHub Copilot (Doe v. GitHub, N.D. Cal. 2022), and OpenAI (multiple plaintiffs, 2023–2024) allege that this constitutes copyright infringement [16]. The EU AI Act (2024) mandates transparency disclosure of copyrighted training materials, establishing an "opt-out" mechanism for rights holders that creator advocacy groups have criticized as operationally impractical at scale.

B. Deepfakes and Information Integrity

The capacity to generate hyper-realistic synthetic media — including face-swapped video, AI-cloned vocal identity, and fabricated images of identifiable individuals — poses material risks to political discourse integrity and personal reputation. Deeptrace Labs (2024) estimated a 900% increase in deepfake content volume between 2020 and 2024, with political disinformation and non-consensual intimate imagery constituting the largest harm categories [17]. The Coalition for Content Provenance and Authenticity (C2PA) cryptographic watermarking standard and deepfake detection model deployment represent early-stage countermeasures, though detection accuracy persistently lags generation sophistication in adversarial conditions.

C. Algorithmic Bias and Cultural Equity

Contemporary generative AI systems exhibit significant performance disparities across languages, cultural traditions, and aesthetic conventions, reflecting the demographic and linguistic bias of dominant training datasets toward Western and English-language content. These disparities represent both an equity concern — systematically underserving the creative workers and audiences of the Global South — and an untapped commercial opportunity for culturally diverse generative systems. Independent bias auditing and mandated training data diversity standards are proposed in both the EU AI Act [16] and WIPO's framework [20].

TABLE III. Ethical Challenges in AI-Generated Creative Content and Proposed Mitigations

Challenge Area	Description	Proposed Mitigation
Copyright Infringement	Training on copyrighted works without licensing or consent [16]	Opt-in datasets, compulsory licensing, C2PA provenance standards
Deepfakes & Disinformation	Synthetic media enabling political deception and fraud [17]	Digital watermarking, deepfake detection models, legal liability

Workforce Displacement	Automation of creative tasks affecting ~8.5M workers globally [18]	Reskilling programs, social safety nets, human-AI collaboration models
Algorithmic Bias	Western/English-language data bias encoding structural inequities	Diverse training datasets, third-party auditing, representation quotas
Environmental Cost	Large model training produces thousands of tonnes CO_2 [19]	Green AI hardware, carbon accounting, efficient model architectures

Sources: EU AI Act 2024 [16]; WIPO AI Policy Framework 2024 [20]; Deeptrace Labs 2024 [17]; McKinsey 2024 [18].

VIII. HUMAN-AI COLLABORATIVE CREATIVE FRAMEWORK (HACF)

Based on the foregoing analysis, this paper proposes the Human-AI Collaborative Creative Framework (HACF), a four-layer operational and governance architecture designed to harness the complementary capabilities of human creative judgment and AI generative power while systematically addressing the identified ethical risks. The framework draws structurally on layered defense-in-depth models proven in information security contexts [cf. Rice, 2020 in the Kubernetes security domain] and adapts them to the creative AI context.

A. Layer 1 — Augmentation

AI tools function as productivity multipliers handling repetitive, technically intensive, or computationally demanding subtasks — texture synthesis, color grading, transcription, translation, metadata tagging, background generation — while human practitioners retain creative direction, conceptual origination, and final quality judgment. This layer addresses the productivity imperative without displacing human creative agency.

B. Layer 2 — Co-Creation

Human practitioners and AI systems engage in iterative generative dialogue: AI proposes creative alternatives, extensions, or variations of human-initiated concepts; human curators evaluate, select, and develop AI outputs within a structured review process. This preserves meaningful human authorship across the generative pipeline while enabling AI to expand the creative solution space.

C. Layer 3 — Attribution and Provenance

All AI-assisted or AI-generated creative content must be labeled using standardized disclosure conventions (C2PA metadata standard), and a blockchain-based provenance registry tracks the relative human and AI contributions throughout the production pipeline. This layer directly addresses copyright attribution ambiguity and consumer transparency obligations under the EU AI Act [16].

D. Layer 4 — Governance and Ethics

An independent AI Creative Ethics Board — comprising working creative professionals, AI researchers, legal scholars, and civil society representatives — establishes enforceable community standards for training data practices, audits deployed systems for bias and copyright compliance, and operates a public redress mechanism for rights violations. The Board operates under principles of transparency, independence, and mandatory triennial external audit.

The HACF positions generative AI as a new creative medium rather than a replacement for human creativity — a framing consistent with historical precedent: photography transformed but did not eliminate painting as an art form; digital audio workstations expanded rather than ended professional musical composition. Generative AI, embedded within the HACF governance structure, is positioned to similarly expand the scope and economic accessibility of creative production.

IX. FUTURE DIRECTIONS

Six priority areas are identified for subsequent research:

1. Longitudinal Labor Market Studies: Rigorous empirical tracking of employment trajectories, skill evolution, and wage dynamics among creative professionals over 5–10-year horizons to ground policy interventions in longitudinal evidence rather than cross-sectional projection.
2. Sustainable AI Infrastructure: Development of carbon accounting standards, energy-efficient training architectures, and hardware co-design

approaches to address the estimated thousands of tonnes of CO_2-equivalent emitted per major generative model training run [19].

3. Cross-Cultural and Multilingual Generative Systems: Model development and fine-tuning programs targeting underrepresented language communities and aesthetic traditions, addressing both equity concerns and commercially underserved markets.
4. Neurocognitive Studies of Human-AI Creative Collaboration: Interdisciplinary research combining cognitive science, human-computer interaction, and creativity science to document how sustained AI collaboration affects human creative cognition, motivation, and long-term skill development.
5. RegTech for Creative AI Compliance: Automated tools for real-time copyright provenance checking, bias auditing, and synthetic media detection deployable at the operational velocity of AI-assisted content production pipelines.
6. Multi-Modal and Embodied Creative AI: Research into generative systems spanning synchronized audio-visual-text generation and physical fabrication (3D printing, robotic art production), extending the domain of AI-assisted creativity beyond screen-based media.

X. CONCLUSION

This paper has presented a systematic analysis of generative AI's impact on creative industries across technical, economic, and ethical dimensions. Three principal deep learning paradigms — Generative Adversarial Networks, Transformer-based Large Language Models enhanced through RLHF fine-tuning, and Latent Diffusion Models — now underpin commercially deployed systems that have measurably altered the economics and practice of creative production across music, visual art, film, writing, advertising, and game development.

The evidence reviewed demonstrates AI adoption rates of 68–90% across major creative sectors, task-specific productivity gains of 35–90%, and a global generative AI market projected to exceed USD 220 billion by 2028 [1][14]. These figures represent a structural transformation rather than a cyclical technology trend. Concurrently, challenges of copyright infringement, deepfake proliferation, algorithmic bias encoding cultural inequity, workforce displacement affecting millions of creative professionals, and unsustainable computational resource consumption require coordinated policy and industry responses proportionate to the scale of the disruption.

The Human-AI Collaborative Creative Framework proposed here offers a practically grounded basis for managing this transformation. Its four governance layers — Augmentation, Co-Creation, Attribution and Provenance, and Ethics Board oversight — provide a structured path toward deploying generative AI in ways that preserve human creative agency, protect intellectual property rights, and distribute economic benefits equitably. Regulatory bodies should prioritize: mandatory training data transparency, legally enforceable provenance standards, proportionate liability frameworks for deepfake harm, and structured investment in reskilling for displaced creative workers. Technology developers should adopt the HACF governance principles as a design constraint rather than an afterthought.

The central empirical finding of this study — that generative AI adoption in creative industries is extensive, economically significant, and structurally transformative — is not in scholarly dispute. What remains open is the governance question: whether the regulatory and institutional frameworks governing creative AI deployment will be designed with sufficient ambition, technical literacy, and respect for creative labor to ensure that this transformation generates broadly shared rather than narrowly concentrated value.

DECLARATIONS

Conflict of Interest:

The authors declare no conflict of interest. No funding was received from commercial AI developers or organizations with a financial interest in the outcomes reported. All product names are used for scholarly identification purposes only.

Ethics Statement:

This study constitutes a secondary research synthesis and did not involve primary data collection from human participants, animal subjects, or personal data. No institutional ethics committee approval was required. All cited survey data were collected and published by independent organizations under their respective ethical review processes. The authors confirm that this paper has not been submitted simultaneously to any other journal.

Data Availability:
This paper does not generate primary research data. All market statistics and survey figures are sourced from published reports listed in the References section.

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