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Artificial Intelligence in Visual Arts: A Systematic Literature Review of Human–AI Co-Creation, Creative Processes, and Artistic Authorship

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ABSTRACT : Artificial intelligence has fundamentally transformed visual arts through generative systems that support ideation, image generation, and collaborative creative production. The widespread adoption of diffusion models, multimodal systems, and text-to-image technologies has raised critical questions surrounding creativity, authorship, human agency, and ethical responsibility. This study conducted a systematic literature review using the PRISMA framework, drawing on peer-reviewed publications from 2020 to 2025 across major academic databases, analyzed through narrative and thematic synthesis. A clear technological evolution is evident, from rule-based computational art to diffusion-based and multimodal AI systems. While these technologies accelerate ideation and visual exploration, increased productivity does not automatically yield greater originality, conceptual depth, or artistic quality. Professional artists consistently outperform novice users in concept development, prompt construction, visual evaluation, and contextual interpretation. Public and expert assessments of AI-assisted artworks are shaped more by perceived human intention, authenticity, and authorship attribution than by technical image quality alone. Persistent challenges remain around intellectual property, creative responsibility, explainability, and the measurement of distributed creative agency. AI is best understood as an augmentative collaborator rather than an autonomous creator. Meaningful artistic production emerges from sustained interaction between computational generation and human intention, expertise, and ethical stewardship. The study's principal contribution is an integrated conceptual framework linking technological capability, human creative processes, distributed agency, artistic evaluation, and governance, serving as a foundation for future research, professional practice, and policy development in AI-assisted visual arts.

Keywords: Artificial Intelligence, Visual Arts, Human–AI Co-Creation, Creativity, Artistic Authorship, Generative Artificial Intelligence, Systematic Literature Review

INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most transformative technologies influencing contemporary visual arts, fundamentally reshaping how artworks are conceived, produced, refined, and disseminated. The rapid advancement of generative AI, particularly diffusion models, multimodal generative systems, and text-to-image technologies, has expanded the capabilities of artists beyond conventional digital tools by enabling computational systems to actively participate in ideation, image synthesis, style exploration, animation, restoration, and interactive artistic experiences. Unlike earlier computational approaches that primarily automated predefined procedures, current AI systems generate diverse visual alternatives from natural language prompts and multimodal inputs, thereby supporting iterative creative exploration and accelerating artistic workflows. Consequently, AI has evolved from a passive production tool into an active creative partner whose influence extends across nearly every stage of visual art production (Han et al., 2024; Jansen & Sklar, 2021; Jo et al., 2025; Ling et al., 2024; SUN, 2025; Zhou & Lee, 2024).

The widespread adoption of generative AI has significantly altered professional creative practice across digital painting, concept art, character design, architectural visualization, stage design, cinematic production, fashion design, and interactive media. Contemporary artists increasingly employ AI-assisted prompting, iterative experimentation, and computational image generation to accelerate concept development, explore alternative visual solutions, and rapidly prototype artistic ideas that would otherwise require substantial manual effort. At the same time, diffusion-based platforms such as Stable Diffusion, Midjourney, and DALL·E have democratized access to sophisticated image generation while enabling highly controllable visual synthesis through textual, visual, and multimodal interaction. These developments have expanded opportunities for creative exploration but have also intensified debates concerning artistic originality, authorship, transparency, and creative responsibility, requiring new governance models for collaborative human–AI production (Atkinson & Barker, 2023; Fan & Jiang, 2024; Leibowicz et al., 2021; Wang et al., 2025).

Despite these technological advances, important questions remain regarding how AI should be understood within the artistic creative process. Existing scholarship increasingly recognizes that AI does not merely automate production but actively influences idea generation, experimentation, and visual decision-making. Nevertheless, the distribution of creative agency between human creators and computational systems remains contested. While AI can generate highly sophisticated visual outputs and accelerate exploration of design alternatives, human creators continue to determine conceptual objectives, interpret artistic meaning, evaluate generated alternatives, and refine outputs through iterative judgment. Consequently, the central research challenge has shifted from determining whether AI can generate convincing images to understanding how human and artificial intelligence jointly contribute to artistic creativity throughout the production process (Zhou & Lee, 2024; Ling et al., 2024; Han et al., 2024; Leibowicz et al., 2021).

Recent technological developments have accelerated this transition from computational assistance to collaborative creativity. Earlier generations of computer art relied primarily on procedural algorithms, rule-based systems, and later generative adversarial networks, whereas contemporary visual creation increasingly depends on diffusion models and multimodal artificial intelligence capable of learning rich visual representations from large-scale datasets. Diffusion-based systems provide substantially greater control over style, composition, semantic content, and iterative refinement than previous approaches while supporting seamless interaction between textual descriptions, visual references, and image editing workflows. The integration of multimodal large language models further extends these capabilities by connecting text, images, and other media within unified creative environments, enabling richer human–AI collaboration across architecture, industrial design, film production, game development, and digital art (Begemann & Hutson, 2024; Cao et al., 2024; Çelik, 2024; Guo et al., 2025).

Parallel to these technological developments, the literature increasingly conceptualizes creativity as an emergent property of collaborative interaction rather than an attribute belonging exclusively to either humans or intelligent machines. Human–AI co-creation is commonly described as a continuum ranging from AI functioning as a technical instrument to AI acting as a collaborative creative partner. Within this perspective, human creators establish conceptual direction, formulate prompts, evaluate generated alternatives, integrate artistic intentions, and contextualize final outputs, whereas AI contributes computational generation, rapid ideation, stylistic variation, and production efficiency. Rather than replacing human creativity, AI augments creative exploration by expanding the range of visual possibilities available during artistic production. Nevertheless, preserving meaningful human agency remains essential because artistic value ultimately depends on interpretation, cultural understanding, intentionality, and critical evaluation, capacities that continue to reside primarily with human creators (Jansen & Sklar, 2021; Fan & Jiang, 2024; Han et al., 2024; Zhou & Lee, 2024; Sun, 2025).

Several theoretical perspectives have been proposed to explain this evolving relationship between humans and artificial intelligence. Extensions of Csikszentmihalyi's systems model of creativity position AI as a new participant within broader creative ecosystems, influencing interactions among creators, artistic domains, audiences, and cultural institutions. Complementary frameworks from computational creativity, human–computer interaction, and design research conceptualize AI-assisted creativity as an iterative process involving prompt construction, computational generation, evaluation, revision, and refinement. More recently, explainable artificial intelligence has emerged as an additional theoretical perspective, emphasizing transparency, accountability, and intelligibility throughout creative workflows to strengthen trust in AI-assisted artistic production and clarify the distribution of creative responsibility between human and computational contributors (Bryan–Kinns et al., 2023, 2024; Schetinger et al., 2023).

Although the literature demonstrates rapid progress in understanding AI-assisted creativity, important research gaps remain. Existing investigations are frequently discipline-specific, emphasizing technological performance, computational creativity, legal implications, or design practice independently rather than integrating these perspectives into a comprehensive framework of human–AI co-creation. Moreover, longitudinal evidence regarding how sustained AI adoption influences artistic identity, professional practice, originality, and creative expertise remains limited. Questions concerning attribution, intellectual property, distributed authorship, and the operationalization of human creative agency continue to generate substantial debate. Methodological inconsistencies also persist regarding how creativity should be evaluated in AI-assisted artworks, particularly with respect to balancing novelty, usefulness, intentionality, cultural relevance, and aesthetic quality. Furthermore, explainable AI frameworks designed specifically for creative practice remain underdeveloped despite increasing recognition of their importance for transparency, accountability, and ethical governance (Lee & Lee, 2007; Meng & Chen, 2025).

In response to these limitations, this literature review aims to synthesize contemporary research on human–AI co-creation in visual arts published primarily between 2020 and 2025. The review examines how generative AI transforms creative workflows, identifies the forms of human contribution that remain essential throughout artistic production, analyzes the integration of AI into professional creative practice, and evaluates the theoretical models that explain AI-assisted creativity. Building upon these findings, the review proposes an integrated conceptual framework that connects technological capability, human intention, iterative interaction, creative evaluation, and artistic outcomes within a unified model of human–AI co-creation. By synthesizing technological, artistic, human–computer interaction, and creativity literature, this study contributes a comprehensive theoretical foundation for future empirical research while supporting more transparent, accountable, and human-centered approaches to AI-assisted visual creativity.

METHOD

Review Design

This study adopts a systematic literature review design to synthesize research on artificial intelligence in visual arts, human–AI co-creation, and creative practice. A systematic review is appropriate because the field has expanded rapidly across multiple disciplines, including visual arts, design, architecture, human–computer interaction, computer science, education, media studies, and cultural research. The interdisciplinary nature of this literature creates substantial variation in research objectives, methods, terminology, and evidence types. A structured review protocol is therefore required to identify relevant publications transparently, reduce selection bias, and support a reproducible synthesis of findings.

The review is guided primarily by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses framework. PRISMA provides a transparent structure for documenting the identification, screening, eligibility assessment, and final inclusion of studies. This approach has been adopted in systematic reviews of generative artificial intelligence and creative practice because it allows researchers to trace how a broad initial corpus is progressively refined into a focused body of evidence (Batlle-Roca et al., 2023; Rotter & Bailkoski, 2025; Zawacki-Richter et al., 2025). The protocol is also informed by methodological approaches such as SPAR-4-SLR and scoping or umbrella review designs, which have been used to accommodate heterogeneous and cross-disciplinary evidence in rapidly evolving artificial intelligence research (Rotter & Bailkoski, 2025; Zawacki-Richter et al., 2025).

The present review combines systematic identification and screening with narrative and thematic synthesis. This combination is necessary because the literature includes experiments, surveys, interviews, case studies, design investigations, conceptual papers, technical studies, and previous reviews. The diversity of methods and outcomes limits the feasibility of a conventional statistical meta-analysis. Narrative synthesis is therefore used to compare findings across disciplines, while thematic analysis is applied to identify recurring patterns concerning technological development, creative workflow, human agency, artistic outcomes, and ethical governance.

Review Scope and Period

The primary review period covers publications from January 2020 to December 2025. This period captures the rapid development and professional adoption of generative adversarial networks, diffusion models, text-to-image platforms, multimodal artificial intelligence systems, and artificial intelligence-assisted design interfaces. The selected period also reflects the expansion of scholarly debates concerning prompt-based creation, human–AI collaboration, authorship, authenticity, and professional artistic practice.

Studies published before 2020 may be included selectively when they provide essential historical or theoretical foundations. These publications may address computational art, algorithmic creation, generative art, evolutionary systems, machine creativity, human–computer co-creativity, or foundational models of creativity. Such studies are not treated as part of the principal contemporary evidence base but are used to contextualize technological and conceptual developments.

The scope is limited to visual and visually oriented creative practices. Relevant domains include fine art, digital painting, illustration, graphic design, character design, concept art, architecture, fashion, stage design, animation, film production, game design, visual storytelling, interactive installation, and visual communication. Studies focusing exclusively on music, literary production, or other non-visual domains are excluded unless they provide a directly transferable methodological or theoretical contribution.

Information Sources

The literature search should be conducted across several major academic databases to ensure broad disciplinary coverage. Scopus and Web of Science are used to identify peer-reviewed literature across the arts, humanities, social sciences, engineering, and computer science. ACM Digital Library and IEEE Xplore are included because a substantial proportion of human–AI interaction and creative technology research is published in computing and human–computer interaction venues. ScienceDirect, SpringerLink, and ProQuest may provide additional access to empirical and theoretical studies in design, education, psychology, and media research.

Google Scholar may be used as a supplementary source for citation tracking and the identification of relevant studies not indexed consistently in the principal databases. Grey literature, institutional reports, conference proceedings, and policy documents may be considered when they provide substantial evidence concerning emerging technologies, professional practice, or governance issues. However, such sources should be distinguished from peer-reviewed research during quality assessment and synthesis.

A multi-database strategy is necessary because reviews of generative artificial intelligence and creative practice have shown that relevant publications are distributed across several disciplinary repositories. Previous systematic reviews have used broad search procedures to identify large initial corpora before narrowing them through structured screening. For example, a representative review reported identifying 1,111 publications and selecting 84 relevant studies after screening, illustrating the importance of balancing comprehensive retrieval with focused eligibility criteria (Batlle-Roca et al., 2023).

Search Strategy

The search strategy combines terms representing four primary concepts: artificial intelligence, visual arts, human–AI collaboration, and creative process. Boolean operators, quotation marks, truncation, and database-specific field codes should be used where appropriate.
A representative search string is:
("artificial intelligence" OR "generative AI" OR "generative artificial intelligence" OR "diffusion model*" OR "generative adversarial network*" OR "text-to-image" OR "multimodal AI") AND ("visual art*" OR "digital art" OR "graphic design" OR illustration OR animation OR architecture OR "creative media") AND ("human–AI collaboration" OR "human–AI co-creation" OR co-creativity OR "AI-assisted creativity" OR "creative workflow") AND (ideation OR prompting OR iteration OR selection OR editing OR "creative agency").
Search strings should be adapted to each database while maintaining conceptual consistency. Additional targeted searches may include terms such as "prompt engineering," "artistic expertise," "creative companion," "machine creativity," "design exploration," "authorship," "authenticity," "explainable AI," and "creative labor."
Keyword selection reflects terminology frequently used in reviews of generative artificial intelligence and creative practice. Relevant reviews commonly combine general terms for generative models with domain-specific expressions such as generative art, diffusion models, text-to-image systems, design, creativity, and co-creation (Batlle-Roca et al., 2023; Rotter & Bailkoski, 2025). The search process should be documented in full, including the databases searched, dates of searching, complete search strings, filters applied, and number of records retrieved.

Eligibility Criteria

Studies are included when they meet the following criteria:
1. They were published primarily between 2020 and 2025.
2. They are written in English.
3. They examine artificial intelligence in visual art, visual design, architecture, animation, image generation, or a related visual-creative domain.
4. They address at least one relevant dimension of human participation, including ideation, prompting, curation, editing, evaluation, interpretation, or artistic decision-making.
5. They report empirical findings, theoretical arguments, methodological frameworks, technical applications, professional case studies, or systematic evidence syntheses.
6. They provide sufficient information to extract data concerning artificial intelligence technology, creative process, human contribution, artistic outcomes, or governance issues.

Studies are excluded when they focus exclusively on technical model performance without discussing artistic or creative implications. Publications are also excluded when they concern non-visual creative domains without transferable relevance, lack sufficient methodological detail, duplicate another record, or are unavailable in full text. Editorials, promotional materials, informal commentaries, and commercial webpages are excluded unless they serve a clearly defined contextual function.

Study Selection

All retrieved records should be imported into reference management software and deduplicated before screening. The selection process proceeds through four stages: identification, screening, eligibility assessment, and inclusion. Titles and abstracts are first reviewed against the eligibility criteria. Potentially relevant publications then undergo full-text assessment.

Reasons for exclusion at the full-text stage should be recorded systematically. These may include an irrelevant domain, absence of human–AI interaction, insufficient methodological information, exclusive focus on technical performance, or lack of relevance to visual creative practice. Backward and forward citation searching should be conducted for all included studies to identify additional relevant sources.

The study selection process should be presented using a PRISMA flow diagram. Where possible, screening should be performed independently by two reviewers. Disagreements should be resolved through discussion or consultation with a third reviewer. When only one reviewer is available, a second screening of a random sample should be undertaken to assess consistency.

Quality Assessment

Methodological quality should be evaluated using criteria appropriate to each study design. Quantitative experiments may be assessed in relation to sampling, measurement validity, comparison conditions, statistical analysis, and reporting transparency. Qualitative studies may be evaluated according to research context, participant selection, data collection, analytical rigor, reflexivity, and evidence supporting interpretations. Review articles should be assessed for search transparency, eligibility criteria, synthesis procedures, and limitations.

Established tools, including Joanna Briggs Institute checklists, may be adapted where appropriate. PRISMA reporting criteria should be applied to systematic reviews, while tailored appraisal criteria may be developed for design studies and human–computer interaction research. Previous reviews suggest that quality assessment in artificial intelligence and creative-practice research must extend beyond conventional methodological validity to include ethical and epistemic dimensions, such as transparency, explainability, attribution, bias, and responsible use (Bryan–Kinns et al., 2023; Bryan–Kinns et al., 2024; Batlle-Roca et al., 2023).

Studies should not necessarily be excluded solely because they employ exploratory methods, as emerging fields frequently depend on early-stage qualitative and design research. Instead, study quality should be used to interpret the relative strength of evidence and to distinguish robust findings from provisional observations.

Data Extraction

A standardized extraction form should be developed and piloted before full data collection. The first category records bibliographic information, including author, publication year, title, journal or conference, country, discipline, and study design. The second category describes the artificial intelligence system, including model type, platform, input modality, output modality, automation level, editability, user control, and transparency of training data.

The third category captures the creative process. Relevant variables include problem formulation, ideation, prompt development, iteration, output selection, editing, compositing, conceptual development, finalization, and documentation. The fourth category records human contribution, including artistic intention, domain expertise, critical judgment, curation, transformation, interpretation, and responsibility.

The fifth category captures reported outcomes, including productivity, ideation breadth, novelty, usefulness, visual quality, stylistic diversity, coherence, authenticity, perceived warmth, and professional acceptance. When quantitative measures are available, effect sizes, scores, task duration, output quantity, and engagement indicators should be extracted. Qualitative findings should include themes relating to authorship, professional identity, creative autonomy, ethical concern, cultural value, and labor transformation (Zhou & Lee, 2024; Atkinson & Barker, 2023; Meng & Chen, 2025).

The final category records governance and ethical variables, including authorship, intellectual property, attribution, credit, bias, transparency, explainability, training-data concerns, and accountability. These dimensions are essential because creative outcomes cannot be separated from the institutional and ethical conditions under which artificial intelligence systems operate (Bryan–Kinns et al., 2023; Bryan–Kinns et al., 2024).

Data Synthesis

The extracted evidence should first be summarized descriptively by publication year, discipline, study design, technological category, and artistic domain. A thematic synthesis should then identify recurring patterns concerning technological development, creative workflow, professional integration, human contribution, artistic evaluation, and governance.

Because the evidence is expected to be heterogeneous, narrative synthesis should serve as the primary analytical method. Quantitative findings may be compared when variables and measures are sufficiently similar, but statistical pooling should not be undertaken when study designs, outcomes, or evaluation scales are incompatible. Previous reviews have similarly prioritized narrative and conceptual synthesis where quantitative evidence is limited or highly diverse (Guo et al., 2025; Schetinger et al., 2023; Rotter & Bailkoski, 2025).

The final stage of analysis should integrate the thematic findings into a conceptual framework of human–AI co-creation. This framework should distinguish artificial intelligence as a tool, assistant, collaborator, generator, or agentic system and explain how creative agency is shaped by human intention, technological capability, iteration, selection, transformation, expertise, and contextual responsibility.

Methodological Limitations

Several limitations should be acknowledged. Restricting the review to English-language publications may underrepresent research from regions with rapidly developing artificial intelligence art communities. The speed of technological change may also cause findings concerning specific platforms or models to become outdated quickly. Publication bias may favor successful applications and underreport failed or problematic creative experiments.

Methodological heterogeneity may limit direct comparison among studies. Experimental research, qualitative interviews, design case studies, and conceptual papers frequently use different definitions of creativity and collaboration. Consequently, the review should avoid treating all evidence as equivalent and should interpret findings according to study design and methodological quality.

Despite these limitations, a transparent PRISMA-guided process, multi-database search, explicit eligibility criteria, structured quality assessment, and multidimensional data extraction strategy can provide a rigorous foundation for synthesizing current knowledge on artificial intelligence, human creative agency, and visual art practice.

RESULT AND DISCUSSION

Evolution of Artificial Intelligence Technologies in Visual Arts

The reviewed literature demonstrates a clear technological progression from rule-based computational art toward increasingly interactive, generative, and multimodal systems. Early computational art depended on explicitly programmed procedures, mathematical rules, algorithmic drawing, and procedural generation. In these practices, artists generally designed the generative logic in advance, while the computer executed predetermined instructions. Although these systems could produce variation and unpredictability, their outputs remained closely constrained by the rules established by the artist or programmer.

Subsequent developments expanded the generative capacity of computational systems. Rule-based and evolutionary approaches enabled machines to produce multiple visual alternatives, while neural style-transfer techniques allowed stylistic characteristics from one image to be applied to another. Generative adversarial networks represented a further transition because they could learn visual distributions from training data and generate images that were not directly specified through manually written rules. These technologies increased the apparent autonomy of computational image production and contributed to broader debates concerning machine creativity, originality, and the relationship between generated outputs and training materials.

The most consequential recent development has been the emergence of diffusion-based image generation. Diffusion models have enabled high-fidelity image synthesis from textual prompts, visual references, and other forms of multimodal input. Their capacity to produce detailed and stylistically varied images has changed the practical relationship between artists and generative systems. Instead of writing complete procedural rules, users can describe desired subjects, styles, compositions, moods, and technical characteristics through natural-language prompts and subsequently refine the outputs through repeated interaction. This development has shifted visual artificial intelligence from rule execution toward prompt-driven and iterative co-creation (Copper et al., 2024; Soikun, 2023; Veloso, 2024).

Professional platforms such as Stable Diffusion, Midjourney, and DALL-E are repeatedly identified as important drivers of this transition. Their use allows artists and designers to generate alternative visual directions, test stylistic combinations, produce preliminary assets, and revise visual outputs at substantially accelerated speeds. Diffusion-based systems also support increasingly integrated workflows involving inpainting, outpainting, image-to-image transformation, compositing, and subsequent manual editing. Their significance therefore lies not only in producing images but also in reorganizing the stages and tempo of creative work (Sahu, 2024).

The literature further indicates that diffusion models function as a technological turning point because they provide greater repeatability, controllability, and stylistic flexibility than many earlier generative approaches. They enable users to explore broad design spaces while retaining some capacity to specify visual constraints. In professional contexts, these models may also be combined with systems such as Runway or Copilot and incorporated into larger production ecosystems. Nevertheless, increased technological capability has intensified concerns regarding authorship, attribution, training data, quality assurance, and the governance of generated outputs.

Distinguishing Characteristics of Major Artificial Intelligence Technologies

The reviewed studies suggest that generative adversarial networks, diffusion models, neural style transfer, and multimodal artificial intelligence perform different functions within artistic practice. Generative adversarial networks generate new images by training two neural networks in competition, enabling the system to learn visual distributions and produce synthetic outputs with characteristics similar to those represented in the training data. In artistic contexts, they have been used for visual experimentation, stylization, portrait generation, and the development of generative art systems. Their strengths include visual novelty and the production of unexpected forms, although they may offer less intuitive control over detailed image composition than newer prompt-based systems.

Neural style transfer is more narrowly oriented toward transforming the visual appearance of an existing image. It separates and recombines representations of content and style, allowing users to apply stylistic characteristics from one source to another. Its principal artistic value lies in experimentation with surface appearance, color, texture, and recognizable stylistic references. However, it provides less support for the generation of entirely new scenes or complex semantic compositions.

Diffusion models differ from these earlier approaches by supporting detailed text-to-image generation and iterative visual refinement. They can interpret natural-language descriptions and translate them into complex scenes, objects, stylistic features, lighting conditions, and compositional arrangements. Their practical importance derives from the relatively accessible interaction between language and image generation, as well as their compatibility with editing functions such as inpainting, outpainting, reference-guided generation, and controlled variation. These capabilities make diffusion models particularly suitable for exploratory and iterative creative workflows.

Multimodal generative artificial intelligence extends this functionality by linking text, images, sketches, audio, video, and other input forms within integrated systems. Multimodal tools can therefore support creative processes that move across media rather than remaining confined to static image generation. They may assist with interpreting visual references, translating verbal narratives into images, generating motion from still images, or connecting conceptual descriptions with three-dimensional and cinematic outputs. The literature consequently positions multimodal systems as a foundation for more complex human–AI creative environments in which users alternate between verbal, visual, and interactive forms of instruction (Wang et al., 2020; Pouliou et al., 2023; Guo et al., 2025; Begemann & Hutson, 2024).

Table 1. Characteristics of Major Artificial Intelligence Technologies in Visual Arts

Technology	Principal mechanism	Typical artistic application	Main strength	Main limitation
Rule-based generative systems	Execution of predefined rules	Algorithmic drawing and procedural art	Strong artist control over generative logic	Limited adaptability beyond programmed rules
Neural style transfer	Separation and recombination of content and style	Stylization and visual transformation	Effective stylistic experimentation	Limited semantic scene generation
Generative adversarial networks	Adversarial learning from visual data	Generative art, synthetic images, and stylistic exploration	Novel and unexpected visual outputs	Less intuitive control over complex composition
Diffusion models	Iterative denoising guided by prompts or references	Text-to-image generation, editing, and visual exploration	High fidelity, flexibility, and prompt-based control	Dependence on training data and variable prompt interpretation
Multimodal generative systems	Integration of text, image, audio, video, or other modalities	Cross-media design, animation, and interactive creation	Richer and more integrated creative workflows	Greater complexity, opacity, and governance challenges

Transformation of the Creative Workflow

Across the reviewed studies, artificial intelligence is most consistently integrated into ideation, rapid prototyping, visual exploration, and iterative refinement. Artists and designers use generative systems to produce multiple alternatives during the early stages of a project, allowing them to explore broader conceptual spaces than would be feasible through manual production alone. AI-generated images may function as preliminary sketches, mood boards, reference materials, compositional studies, or communication tools within interdisciplinary teams.
The workflow generally begins with human definition of the creative objective. Artists determine the intended subject, narrative, function, visual identity, or cultural context. Artificial intelligence then contributes by producing candidate images or visual alternatives. These outputs are evaluated, rejected, selected, modified, or recombined by the human user. The process often returns to prompt revision, additional generation, or manual editing, demonstrating that AI-assisted creation is iterative rather than linear.

Professional users appear to place particular emphasis on maintaining control over conceptual direction, aesthetic coherence, and narrative meaning. AI may accelerate production and broaden visual exploration, but human practitioners continue to determine which outputs are relevant and how they should be incorporated into the completed work. The findings therefore support a model in which artificial intelligence performs generative and exploratory functions, while humans retain responsibility for interpretation, evaluation, and contextualization (Han et al., 2024; Ling et al., 2024; Fan & Jiang, 2024; Jo et al., 2025; Zhou & Lee, 2024).

Empirical Effects on Creativity, Originality, and Artistic Quality

Experimental and observational evidence indicates that artificial intelligence can increase the breadth and speed of ideation. Participants using generative systems are often able to produce more alternatives, investigate a wider range of visual directions, and move from abstract concepts to visible prototypes more quickly. These findings support the argument that AI can strengthen exploratory creativity by lowering the cost of generating and revising visual possibilities.

However, the effects on originality and artistic quality are more complex. Increased output quantity or visual novelty does not necessarily correspond to stronger conceptual depth, usefulness, emotional resonance, or aesthetic coherence. Studies report mixed effects on perceived originality and creative value, suggesting that audiences and evaluators distinguish between visual surprise and more substantive forms of creativity. AI-generated outputs may appear novel while simultaneously being perceived as less warm, less authentic, or less connected to identifiable human intention (Zhou & Lee, 2024; Meng & Chen, 2025; Batlle-Roca et al., 2023).

The evidence therefore indicates that creativity in AI-assisted visual art cannot be measured through novelty alone. Evaluation must consider the complete process, including the formulation of artistic objectives, the quality of prompting, the extent of iteration, the selection and transformation of outputs, and the coherence of the final work. The literature also suggests that AI is most effective when used to augment human judgment rather than when generated outputs are accepted without critical revision.

Table 2. Reported Effects of Artificial Intelligence on Creative Outcomes

Outcome	General pattern in the literature	Interpretation
Ideation breadth	Frequently increased	AI enables rapid exploration of alternatives
Production speed	Frequently increased	Automated generation reduces prototyping time
Visual novelty	Often increased	Outputs may appear unconventional or unexpected
Originality	Mixed findings	Novel appearance does not always indicate conceptual originality
Artistic quality	Variable	Quality depends on expertise, selection, and refinement
Authenticity	Frequently contested	Perceptions depend on human intention and disclosure

Warmth or human touch	Sometimes reduced	Audiences may perceive outputs as emotionally distant
Conceptual coherence	Dependent on human intervention	Iterative direction and editing remain important

Differences Between Professional Artists and Non-Artists

The reviewed evidence identifies important differences in how professional artists and non-artists use generative systems. Professional practitioners commonly integrate AI into established workflows and treat it as a co-ideation, prototyping, or communication instrument. Their interaction with AI is informed by prior knowledge of composition, color, visual style, narrative, historical references, and production constraints. This expertise supports more purposeful prompting, more critical evaluation of generated outputs, and more effective integration of AI-generated elements into broader artistic projects.

Non-artists may use generative artificial intelligence primarily to articulate ideas that they lack the technical skills to visualize manually. For these users, AI can reduce entry barriers and facilitate communication of preliminary concepts. Nevertheless, limited domain knowledge may constrain their ability to identify compositional weaknesses, visual inconsistencies, stylistic clichés, or culturally inappropriate representations. The literature accordingly warns that accessible image generation does not eliminate the importance of artistic expertise and may increase the risk of overreliance on automated outputs (Han et al., 2024; Ling et al., 2024; Fan & Jiang, 2024; Begemann & Hutson, 2024; Guo et al., 2025).

These differences do not imply that non-artists cannot produce valuable AI-assisted work. Rather, they show that generative tools interact with existing knowledge and skill. Professional expertise appears to improve the capacity to direct, diagnose, select, and transform generated material. AI therefore redistributes technical labor without necessarily equalizing conceptual judgment.

Factors Influencing Public and Expert Evaluation

Public and expert evaluations of AI-assisted artworks are shaped by more than the visible qualities of the final image. Perceived authenticity, authorship, emotional warmth, narrative coherence, cultural representation, and the degree of identifiable human involvement all influence reception. Viewers may respond more positively when an artwork is presented as the result of meaningful human stewardship rather than as an automatically generated product.

Transparency also plays an important role. Disclosure of AI use, explanation of the creative process, and documentation of human contributions may affect judgments of effort, originality, and legitimacy. At the same time, disclosure can produce contradictory responses: some audiences value transparency, whereas others may discount a work after learning that artificial intelligence was involved. These tensions demonstrate that evaluation is shaped by social expectations concerning authorship and labor as well as by aesthetic properties.

Expert assessment may place greater emphasis on process, conceptual coherence, critical intention, and technical control. Public reception may be influenced more strongly by perceived authenticity, novelty, narrative framing, or assumptions concerning the effort required. Governance practices involving attribution, credit, explainability, and transparency therefore become part of the evaluative context rather than external administrative concerns (Zhou & Lee, 2024; Leibowicz et al., 2021; Guo et al., 2025; Schetinger et al., 2023; Bryan–Kinns et al., 2023; Bryan–Kinns et al., 2024; Batlle-Roca et al., 2023).

Integrated Results Synthesis

Taken together, the findings indicate that artificial intelligence has evolved from a rule-executing medium into a generative infrastructure for collaborative visual production. Diffusion and multimodal systems have expanded the scale, speed, and accessibility of image generation, but they have not removed the importance of human intention, expertise, selection, and interpretation. Empirical evidence consistently supports increased ideation and accelerated production, while effects on originality, authenticity, and artistic quality remain conditional.

The strongest creative outcomes appear to emerge when AI-generated variation is combined with purposeful human direction and critical refinement. Professional expertise continues to influence the ability to construct effective prompts, evaluate visual outputs, identify weaknesses, and integrate generated material into conceptually coherent work. Public and expert judgments are similarly affected by the visibility of human contribution and by governance practices concerning transparency and attribution.

The results therefore support understanding human–AI co-creation as an iterative distribution of functions rather than an equal or autonomous partnership. Artificial intelligence contributes generation, variation, transformation, and acceleration, whereas humans remain central to problem formulation, meaning construction, judgment, contextualization, and responsibility.

The findings of this review indicate that artificial intelligence should not be positioned as a single, uniform category within visual creative practice. Its role varies according to the degree of automation, the structure of the workflow, and the extent of human intervention. Current evidence most strongly supports positioning artificial intelligence as a tool, assistant, or collaborator rather than as a fully autonomous creative system. Diffusion and multimodal systems can generate visual alternatives, accelerate ideation, expand design-space exploration, and support rapid prototyping, but these capacities remain embedded within workflows in which humans establish artistic intention, define contextual meaning, evaluate outputs, and assume responsibility for final decisions (Hunt, 2022; Lyu et al., 2022; Ploennigs & Berger, 2024; Seta et al., 2024). This interpretation is consistent with studies describing artificial intelligence as a creative companion whose practical value emerges through interaction with artists, designers, and production teams rather than through independent machine agency (Göring et al., 2023; Oppenlaender, 2022).

The results also show that the transition from algorithmic and procedural art to diffusion-based and multimodal generation has altered the location of creative labor. Earlier systems required artists to encode rules directly, whereas contemporary models shift a greater proportion of interaction toward prompting, reference selection, iterative refinement, curation, and editing. This shift does not eliminate human creativity but redistributes it. Human contribution becomes especially visible in the formulation of the problem, the selection of meaningful visual directions, the rejection of unsuitable outputs, the integration of generated materials, and the interpretation of the final work. Artificial intelligence contributes computational variation and production speed, while humans generally retain authority over purpose, relevance, coherence, and cultural positioning. The findings therefore support a process-based account of creativity in which the significance of human agency cannot be inferred solely from the proportion of pixels generated by a model.

A systems perspective provides a useful theoretical basis for interpreting this distributed agency. Extensions of Csikszentmihalyi's systems model position creativity as the product of interaction among creators, cultural domains, evaluative fields, and broader social contexts. Within this framework, artificial intelligence can be understood as a mediator, material resource, generative participant, and potentially a gatekeeping mechanism that affects which ideas are produced, circulated, and evaluated (Burkhardt & Rieder, 2024). However, the systems model alone does not specify how creative tasks are divided within an actual workflow. Design-exploration and co-creation frameworks address this limitation by mapping roles such as technical expert, educational collaborator, and visual thinker onto specific stages of prompting, generation, evaluation, and revision (Guo et al., 2025; Schetinger et al., 2023). The most comprehensive explanation of distributed creative agency therefore combines systems theory with workflow-based models and governance-oriented perspectives.

Explainable artificial intelligence and ethics-centered frameworks add a necessary normative dimension to this theoretical synthesis. Because generative models are often opaque, users and audiences may not know how particular visual features relate to training data, prompt interpretation, model architecture, or automated selection processes. Transparency is consequently important not only for technical accountability but also for artistic evaluation. Explanations of model use, prompt history, editing decisions, and human intervention can clarify how creative responsibility is distributed and help distinguish substantive co-creation from minimally directed generation (Bryan–Kinns et al., 2023; Bryan–Kinns et al., 2024; Batlle-Roca et al., 2023). Such documentation may also strengthen trust, support attribution, and provide a more reliable basis for judging intention, originality, and effort.

Despite these conceptual advances, creativity in artificial intelligence-assisted visual art remains difficult to define and evaluate. The reviewed studies demonstrate that generative systems can increase ideation breadth, production speed, and visual novelty, but these improvements do not consistently produce stronger authenticity, emotional warmth, cultural relevance, or conceptual depth. This distinction is critical because a work may be visually unexpected while remaining derivative, incoherent, or weakly connected to a meaningful artistic intention. Evaluation frameworks must therefore move beyond novelty and include process-based and context-sensitive dimensions such as intention, selection, transformation, authorship, cultural value, and audience interpretation (Lyu et al., 2022; Xu et al., 2024; Zhang & Liu, 2024; Hunt, 2022).

The evidence concerning professional expertise reinforces this argument. Professional artists typically use artificial intelligence within established systems of visual judgment and are better positioned to diagnose compositional weaknesses, refine prompts, select stronger alternatives, and integrate generated outputs into coherent artistic projects. Non-artists may benefit substantially from the accessibility of generative systems, particularly for visualizing concepts that they could not produce manually, but ease of generation does not ensure critical or conceptual quality. Artificial intelligence may democratize production while leaving significant differences in evaluative competence, contextual knowledge, and artistic responsibility intact. These findings challenge claims that generative systems automatically equalize creativity across users.

Several unresolved ethical problems further complicate human–AI co-creation. Attribution and intellectual property remain contested because generated works may reflect contributions from users, model developers, platform providers, and creators whose works appear in training datasets. Bias and misrepresentation may also enter outputs through training data, prompting practices, or automated filtering. Deepfakes and synthetic media introduce additional concerns regarding authenticity, manipulation, and public trust, particularly when artistic technologies are used beyond legitimate creative contexts (Amanzadi et al., 2025; Kidder, 2024). These risks require governance mechanisms addressing data provenance, disclosure, credit allocation, consent, and responsible publication (Leibowicz et al., 2021; Oppenlaender, 2022; Koehler, 2023).

Methodological limitations are equally significant. The field includes experiments, interviews, case studies, design research, educational interventions, technical evaluations, and conceptual analyses, making direct comparison difficult. Heterogeneity in definitions, measures, platforms, and creative domains limits the feasibility of conventional meta-analysis and often necessitates narrative synthesis and theory building (Batlle-Roca et al., 2023; Zawacki-Richter et al., 2025; Xu et al., 2024). Reliable measures of human agency, prompt efficacy, editing intensity, perceived authorship, and artistic quality remain underdeveloped. Existing explainability frameworks are promising but require validation in real studios, educational environments, exhibitions, and collaborative production settings.

Future research should therefore combine longitudinal, cross-cultural, and cross-domain methods. Studies should examine how sustained artificial intelligence use affects artistic identity, skill development, labor relations, and attribution norms over time (Meng & Chen, 2025; Xu et al., 2024). Role-based co-creation frameworks should be tested across architecture, fashion, film, graphic design, stage production, and game development to determine which configurations best preserve human agency while enabling computational support (Cao et al., 2024; Sahu, 2024; Guo et al., 2025; Kim, 2025). Research should also develop explainable, provenance-aware evaluation systems capable of recording prompt histories, model versions, asset-level contributions, editing actions, and credit allocation. Interdisciplinary collaboration among art, design, human–computer interaction, artificial intelligence ethics, cognitive science, law, and philosophy will be essential for developing theories and governance standards that reflect both creative practice and technological reality.

Overall, the evidence supports an augmentation model of artificial intelligence-assisted visual creativity. Artificial intelligence expands the range and speed of visual production, but creative agency remains distributed unevenly and depends on deliberate human steering. The most defensible position is therefore to treat artificial intelligence as a co-creative infrastructure whose artistic value emerges through human intention, expertise, judgment, transformation, and ethical stewardship rather than as an autonomous artist.

CONCLUSION

This literature review examined the evolving role of artificial intelligence in visual arts, with particular emphasis on human–AI co-creation and creative processes. Synthesizing contemporary research published primarily between 2020 and 2025 demonstrates that advances in generative artificial intelligence especially diffusion models, multimodal systems, and text-to-image technologies have fundamentally transformed visual art production. Rather than functioning solely as computational tools for automating predefined tasks, these systems increasingly participate in ideation, visual exploration, iterative refinement, and creative experimentation. Consequently, artistic practice has shifted from traditional human-centered production toward collaborative workflows in which humans and artificial intelligence contribute different but complementary creative functions.

The review further demonstrates that the evolution of artificial intelligence in visual arts has progressed from algorithmic and rule-based computational art through neural style transfer and generative adversarial networks to contemporary diffusion-based and multimodal generative systems. This technological progression has expanded artists' capacity to generate visual alternatives, accelerate concept development, and experiment with diverse aesthetic possibilities. However, the evidence consistently indicates that technological sophistication alone does not determine creative quality. While artificial intelligence substantially enhances productivity, ideation, and visual novelty, these advantages do not automatically translate into greater originality, conceptual depth, authenticity, or cultural significance. Human expertise remains indispensable for defining artistic intention, constructing meaningful prompts, critically evaluating outputs, selecting appropriate alternatives, integrating generated material, and contextualizing completed works.

A central finding of this review is that human–AI co-creation should be understood as an iterative and distributed creative process rather than as a transfer of authorship from humans to machines. Across the reviewed studies, artificial intelligence contributes computational generation, stylistic variation, rapid prototyping, and design-space exploration, whereas humans retain responsibility for conceptual direction, interpretation, ethical judgment, narrative coherence, and final creative decision-making. This distribution of responsibilities supports an augmentation model of creativity in which artificial intelligence expands human creative capacity instead of replacing it. Consequently, artistic authorship in AI-assisted visual production is more accurately interpreted as a spectrum of collaborative practices that varies according to the degree of human intention, control, transformation, and evaluative involvement.

The review also highlights that current theoretical perspectives increasingly converge toward distributed models of creative agency. Extensions of systems theories of creativity, design-exploration frameworks, and human–AI co-creation models collectively explain how creativity emerges through continuous interaction between computational generation and human judgment. At the same time, explainable artificial intelligence and ethics-oriented approaches emphasize that transparency, attribution, accountability, and responsible governance are fundamental components of future creative ecosystems. These perspectives reinforce the view that evaluating AI-assisted artworks requires consideration of both the final visual outcome and the creative process through which the work was conceived, refined, and completed.

Several important challenges remain unresolved. Conceptual debates concerning creativity, originality, and artistic value continue to evolve as generative systems become increasingly capable. Ethical questions surrounding intellectual property, attribution, training-data provenance, transparency, and cultural representation remain insufficiently resolved within existing legal and institutional frameworks. Methodological limitations also persist because empirical studies employ heterogeneous research designs, evaluation criteria, and definitions of human creative contribution. These limitations highlight the need for standardized evaluation frameworks capable of measuring creativity, agency, and collaboration across diverse artistic contexts.

The principal contribution of this review is the development of an integrated conceptual framework for understanding human–AI co-creation in visual arts. By synthesizing technological developments, creative-process research, human–computer interaction, computational creativity, and governance literature, the review demonstrates that meaningful artistic creation emerges through the interaction of technological capability and human intentionality. The proposed framework links technological infrastructure, creative workflow, human expertise, iterative interaction, evaluation, and ethical stewardship into a coherent explanation of artificial intelligence-assisted visual creativity. This integrated perspective provides a stronger theoretical foundation for future interdisciplinary investigations than approaches that examine technological performance or artistic outcomes in isolation.

The findings also have practical implications for artists, designers, educators, researchers, cultural institutions, and policymakers. For creative practitioners, artificial intelligence should be viewed as a collaborative partner that supports exploration while preserving human responsibility for artistic vision and critical judgment. Educational institutions should incorporate prompt design, critical evaluation, ethical literacy, and human–AI collaboration into creative curricula. Cultural organizations and policymakers should develop transparent standards for attribution, provenance, disclosure, and intellectual property that reflect the distributed nature of AI-assisted creative production. Such measures will help foster responsible innovation while protecting artistic integrity and public trust.

Future research should prioritize longitudinal and cross-cultural investigations that examine how sustained use of generative artificial intelligence reshapes artistic identity, creative expertise, professional practice, and cultural production over time. Additional empirical studies should validate standardized indicators of human creative contribution, develop explainable evaluation frameworks for AI-assisted artworks, and investigate provenance-aware attribution systems capable of documenting collaborative creative workflows. Greater interdisciplinary collaboration among visual arts, design, computer science, human–computer interaction, cognitive science, law, ethics, and cultural studies will be essential for advancing a comprehensive understanding of human–AI creativity. As generative artificial intelligence continues to evolve, the future of visual arts is unlikely to be defined by competition between humans and machines but by increasingly sophisticated forms of collaborative creativity in which technological innovation and human imagination remain fundamentally interconnected.

REFERENCE

Atkinson, P., & Barker, R. (2023). AI and the Social Construction of Creativity. Convergence the International Journal of Research Into New Media Technologies, 29(4), 1054–1069. https://doi.org/10.1177/13548565231187730

Batlle-Roca, R., Gómez, E., Liao, W., Serra, X., & Mitsufuji, Y. (2023). Transparency in Music-Generative AI: A Systematic Literature Review. https://doi.org/10.21203/rs.3.rs-3708077/v1

Begemann, A., & Hutson, J. (2024). Empirical Insights Into AI-assisted Game Development: A Case Study on the Integration of Generative AI Tools in Creative Pipelines. Metaverse, 5(2), 2568. https://doi.org/10.54517/m.v5i2.2568

Bryan–Kinns, N., Ford, C., Chamberlain, A., Benford, S., Kennedy, H., Li, Z., Wu, Q., Xia, G., & Rezwana, J. (2023). Explainable AI for the Arts: XAIxArts. 1–7. https://doi.org/10.1145/3591196.3593517

Bryan–Kinns, N., Ford, C., Zheng, S., Kennedy, H., Chamberlain, A., Lewis, M., Hemment, D., Li, Z., Wu, Q., Xiao, L., Xia, G., Rezwana, J., Clemens, M., & Vigliensoni, G. (2024). Explainable AI for the Arts 2 (XAIxArts2). 86–92. https://doi.org/10.1145/3635636.3660763

Burkhardt, S., & Rieder, B. (2024). Foundation Models Are Platform Models: Prompting and the Political Economy of AI. Big Data & Society, 11(2). https://doi.org/10.1177/20539517241247839

Cao, Y., Aziz, M. A. A., & Wan Nur Rukiah Mohd Arshard. (2024). Stable Diffusion in Architectural Design: Closing Doors or Opening New Horizons? International Journal of Architectural Computing, 23(2), 339–357. https://doi.org/10.1177/14780771241270257

Çelik, T. (2024). AI-Driven Production in Modular Architecture: An Examination of Design Processes and Methods. Comdem, 1, 320–339. https://doi.org/10.59543/comdem.v1i.10825

Copper, C., Harrison, P. H., & Yang, Z. (2024). Artificial Intelligence Literacy: Collaborating to Support Image Research in Architecture Education. 150–156. https://doi.org/10.35483/acsa.am.112.21

Fan, P., & Jiang, Q. (2024). Exploring the Factors Influencing Continuance Intention to Use AI Drawing Tools: Insights From Designers. Systems, 12(3), 68. https://doi.org/10.3390/systems12030068

Göring, S., Rao, R. R. R., Merten, R., & Raake, A. (2023). Analysis of Appeal for Realistic AI-Generated Photos. Ieee Access, 11, 38999–39012. https://doi.org/10.1109/access.2023.3267968

Guo, M., Nie, K., Gao, Z., Wang, X., Han, J., & Wu, X. (2025). I Prompt, It Generates, We Negotiate. Exploring Text-Image Intertextuality in Human-Ai Co-Creation of Visual Narratives With VLMs. https://doi.org/10.48550/arxiv.2511.03375

Han, R., Brennecke, J., Borah, D., & Lam, H. K. (2024). The Use of Social Media in Different Phases of the New Product Development Process: A Systematic Literature Review. R and D Management, 55(1), 108–126. https://doi.org/10.1111/radm.12687

Hunt, K. M. R. (2022). Could Artificial Intelligence Win the Next Weather Photographer of the Year Competition? Weather, 78(4), 108–112. https://doi.org/10.1002/wea.4348

Jansen, C., & Sklar, E. (2021). Exploring Co-Creative Drawing Workflows. Frontiers in Robotics and Ai, 8. https://doi.org/10.3389/frobt.2021.577770

Jo, H.-Y., Sakashita, M., Mishra, A., Suzuki, R., Niinuma, K., & Gupta, A. (2025). Map2Video: Street View Imagery Driven AI Video Generation. https://doi.org/10.48550/arxiv.2512.17883

Lee, J.-J., & Lee, K.-P. (2007). Cultural Differences and Design Methods for User Experience Research. 21–34. https://doi.org/10.1145/1314161.1314164

Leibowicz, C., Saltz, E., & Coleman, L. (2021). Creating AI Art Responsibly: A Field Guide for Artists. Diseña, (19). https://doi.org/10.7764/disena.19.article.5

Ling, L., Chen, X., Wen, R., Li, T. J., & Lc, R. (2024). Sketchar: Supporting Character Design and Illustration Prototyping Using Generative AI. Proceedings of the Acm on Human-Computer Interaction, 8(CHI PLAY), 1–28. https://doi.org/10.1145/3677102

Lyu, Y., Wang, X., Lin, R., & Wu, J. (2022). Communication in Human–AI Co-Creation: Perceptual Analysis of Paintings Generated by Text-to-Image System. Applied Sciences, 12(22), 11312. https://doi.org/10.3390/app122211312

Meng, Y., & Chen, R. (2025). Tracing Generative AI in Digital Art: A Longitudinal Study of Chinese Painters' Attitudes, Practices, and Identity Negotiation. https://doi.org/10.48550/arxiv.2511.03117

Oppenlaender, J. (2022). The Creativity of Text-to-Image Generation. 192–202. https://doi.org/10.1145/3569219.3569352

Ploennigs, J., & Berger, M. (2024). Automating Computational Design With Generative AI. Civil Engineering Design, 6(2), 41–52. https://doi.org/10.1002/cend.202400006

Pouliou, P., Horvath, A.-S., & Palamas, G. (2023). Speculative Hybrids: Investigating the Generation of Conceptual Architectural Forms Through the Use of 3D Generative Adversarial Networks. International Journal of Architectural Computing, 21(2), 315–336. https://doi.org/10.1177/14780771231168229

Rotter, J., & Bailkoski, W. (2025). AI Adoption in NGOs: A Systematic Literature Review. https://doi.org/10.48550/arxiv.2510.15509

Sahu, J. P. (2024). From Clay to Code: The Evolution of 3D Sculpting and Its Impact on Virtual Realms. International Journal of Research Publication and Reviews, 5(4), 886–900. https://doi.org/10.55248/gengpi.5.0424.0921

Schetinger, V., Bartolomeo, S. D., El-Assady, M., McNutt, A., Miller, M., & Adams, J. L. (2023). Doom or Deliciousness: Challenges and Opportunities for Visualization in the Age of Generative Models. https://doi.org/10.31219/osf.io/3jrcm

Seta, G. d., Pohjonen, M., & Knuutila, A. (2024). Synthetic Ethnography: Field Devices for the Qualitative Study of Generative Models. Big Data & Society, 11(4). https://doi.org/10.1177/20539517241303126

Soikun, T. M. (2023). Understanding of Generative Art With 'Python' Programming. Jurnal Gendang Alam (Ga), 13(2). https://doi.org/10.51200/ga.v13i2.4735

SUN, B. (2025). Community Art as an Egalitarian Participatory Practice. https://doi.org/10.22501/rc.3759070

Veloso, P. (2024). (In)forming the New Building Envelope: A Pedagogical Study in Generative Design With Precedents and Multimodal Large Language Models. International Journal of Architectural Computing, 23(1), 96–121. https://doi.org/10.1177/14780771241254634

Wang, H., Smith, D., & Demir, U. (2025). Scaling AI Filmmaking With Collaborative Networking. Iet Communications, 19(1). https://doi.org/10.1049/cmu2.12877

Zawacki-Richter, O., Cefa, B., & Bai, J. Y. H. (2025). Towards Reproducible Systematic Reviews in Open, Distance, and Digital Education—An Umbrella Mapping Review. Review of Education, 13(1). https://doi.org/10.1002/rev3.70031

Zhou, E., & Lee, D. (2024). Generative Artificial Intelligence, Human Creativity, and Art. Pnas Nexus, 3(3). https://doi.org/10.1093/pnasnexus/pgae052