From Style Replication to Style Exploration: Enabling Art Style Exploration with Analyze-Experiment-Resituate Framework

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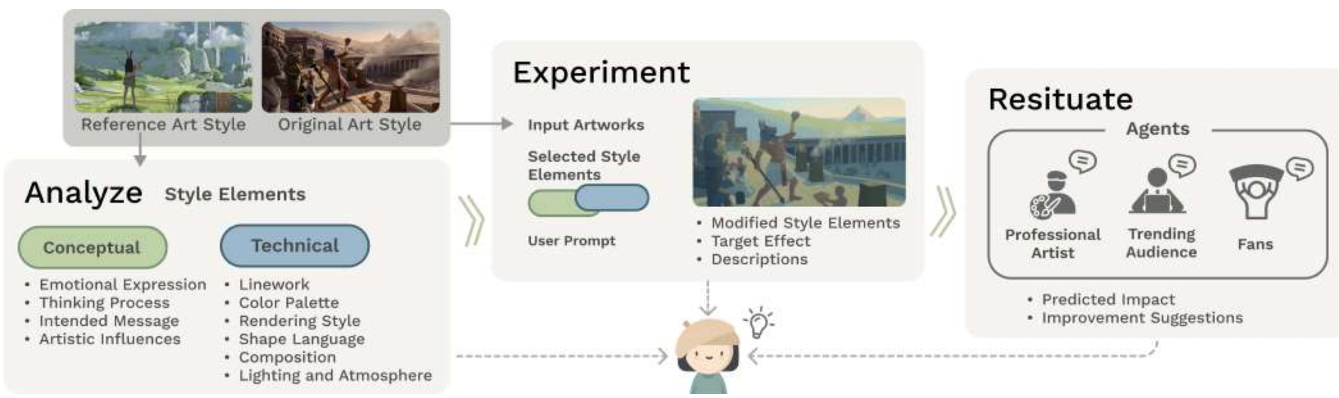

Figure 1: The Analyze-Experiment-Resituate (AER) framework. Existing GenAI tools encourage style replication over exploration. To enable professional artists to explore a new art style with GenAI, we developed the AER framework based on interviews with 10 professional digital artists. The AER framework allows artists to analyze both the conceptual and technical elements of a reference artwork during the *Analyze* stage. In the *Experiment* stage, it enables artists to experiment with new styles by employing prompt engineering and selecting pre-decomposed style elements. Additionally, in the *Resituate* stage, it provides simulated feedback from role-based agents, including professional artists, audiences, and fans. This feedback helps artists reassess their developing styles from multiple perspectives.

Abstract

Art style is a signature of professional digital artists that develops through repeated experimentation, reflection, and adaptation. While generative AI (GenAI) can reproduce styles with high fidelity, current tools provide limited support for exploring new stylistic directions and may encourage style replication over exploration. To address this gap, we propose *Analyze-Experiment-Resituate (AER)*, a framework for AI-assisted style exploration derived from interviews with 10 professional digital artists. Rather than prioritizing visually appealing outputs alone, AER supports three core practices of style exploration, including interpreting references, trying out stylistic possibilities, and reflecting on how emerging styles may be received. Specifically, AER enabled artists to (1) analyze artworks into interpretable stylistic elements, (2) have controllable experimentation guided by their own choices, and (3) resituate emerging styles through simulated social perspectives. We implemented AER in a prototype system and evaluated it in a controlled experiment study with 16 artists. Compared with a direct style-transfer workflow, AER increased artists' agency and reflection as they pursued new stylistic directions. A two-week field study with four artists revealed how the AER framework influenced daily style exploration, such as reflection, experimentation, and stylistic decision-making at each stage. We discuss opportunities and challenges in designing AI-assisted style-exploration workflows, and outline implications for future artistic support tools.

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CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**; **User centered design**.

Keywords

Art Style Exploration; Artistic Support Tool; AI-assisted Creativity Support Tool; Field Study

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1 Introduction

Art style is the soul of professional visual creation. For digital artists like illustrators and concept artists, style functions not only as a recognizable visual signature, but also a way of expressing artistic identity [1], emotional intent [34], and creative thinking through recurring visual and conceptual choices [56, 68]. In artists' creative practice and long-term development, style exploration is therefore an iterative process in which they study references, experiment with techniques and stylistic directions, reflect on their creative decisions, and incorporate feedback from other peers [30, 38, 44, 68].

In the digital era, the style exploration process has been accelerated by tools that expand access to references and enable faster style experimentation. For instance, digital painting tools support efficient iteration with brushes, palettes, and rendering techniques [5], while online platforms expose artists to a much broader range of visual material and creative influences [82]. Generative AI (GenAI) further extends these possibilities by enabling rapid ideation [16, 82, 84], image refinement [64, 81], and exploration of visual alternatives [75, 82]. However, prior research has focused on supporting ideation or improving the speed and quality of image generation, while the design space for supporting style exploration remains underexplored.

In much of AI research, style is operationalized as a set of aesthetic features that can be copied, transferred, or reproduced across images [65]. This view differs from how artists experience style in practice: not as a fixed visual property, but as an evolving and situated aspect of creative work [52] that requires substantial time, reflection, and iterative exploration. Current GenAI tools also tend to prioritize stylistic outputs over artists' interpretation and decision-making, reducing their sense of control and authorship [41, 45]. As a result, while there are many GenAI-based tools for creativity support, existing AI support offers limited value for style exploration.

Therefore, this work employed three studies to investigate the design space of GenAI-supported style exploration for professional illustrators and concept artists. We focused on illustrators and concept artists because they must continuously adapt their style to the needs of fans, audiences, and clients while maintaining a distinct artistic voice. First, we started by understanding artists' current practices and challenges when developing a new style. We asked, ***what motivations, strategies, and challenges influence professional illustrators' and concept artists' style exploration practices?*** **(RQ1)** In the formative study, we examined how these artists explore and evolve their personal art style. We then developed an interaction framework, *Analyze-Experiment-Resituate* (AER), to inform the design of GenAI for style exploration based on the interview findings. Next, we conducted a within-subjects experiment with 16 professional illustrators and concept artists to examine how this AER framework influences style exploration compared with a direct AI-generated style transfer workflow. In the controlled experiment study, we answered, ***how does the proposed AER framework influence artists' agency and reflection during style exploration?*** **(RQ2)** Finally, we implemented this framework on a web platform and evaluated its influence on artists' style exploration processes and stylistic decision-making in their daily practice. We conducted a two-week field study with two professional illustrators and two professional concept artists, aiming to answer: ***how do artists engage with the AER framework over time during style exploration?*** **(RQ3)**

Our contributions include an empirical account of visual artists' practices in exploring styles (formative study), an interaction framework to guide the design of creativity-support tools specifically for AI-assisted style exploration (controlled experiment study and field study), and a demonstration of how GenAI can be designed to enable visual artists to analyze, experiment, and reflect during their style exploration without compromising their creative agency. Together, these contributions shift the role of GenAI in creative practice from merely producing *stylistic outputs* as part of a supply chain toward supporting an artist-led *process* in style exploration, enabling more open interpretation and reflection.

2 Related Work

2.1 Process Matters in Style Exploration for Artists

For digital artists, style serves as both a recognizable signature and a marker of creative identity [62, 67]. It facilitates recognition by allowing audiences and clients to identify an artist's work through recurring attributes such as color palettes, textures, strokes, and compositional patterns [61, 79]. Style embodies an artist's thinking process, personal expression, influences, and communicative intent [31, 33, 46]. Furthermore, style also has a social dimension, connecting artists with cultural lines and communities while distinguishing them in professional contexts [26, 71]. Based on these characteristics, this study defines *style* as the visual, conceptual, and social signature of an artist.

The process of artists exploring style is defined as a continuous, recurring cycle, in which artists engage in a dynamic dialog between reference work, the tools and creative medium [32]. It is a non-linear longitudinal process that often spans years, during which artists continuously adapt their style in the actual making of the art. This exploratory process involves the analysis of prior works and the reflection on feedback to iterate the style [41, 52, 65].

Within the field of digital arts, existing study centers around the artifact-centric process of artwork production, which often focuses on the workflow of creating a specific work [76, 80]. However, the digital support available to artists to explore new styles remains under-examined. Our work addresses this gap by empirically examining digital artists' practices in style exploration, shifting the focus of creativity-support tools from artifact production to the process of style evolution.

2.2 The Invisible Process and Outcome-centered Style Transfer in GenAI-based Tools

Computational research has largely treated style as a transferable set of visual attributes, defined as a set of computationally reproducible factors, such as color and texture [39, 52, 66]. Treating style as a quantifiable set of visual features lays the computational foundation for style transfer research.

Conceptually, style transfer involves extracting stylistic components from a reference image and applying them to other images. Early milestones such as Hertzman's Image Analogies [37], framed style transfer as learning transformations from paired examples. This is followed by Gatys et al.'s Neural Style [29], which disentangles content and style using CNNs, and Johnson et al.'s feed-forward networks for real-time performance [43]. Subsequent advances included GAN-based models for paired and unpaired translation, and diffusion models that made text-to-style generation broadly accessible, with ControlNet preserving structure fidelity while altering style [86]. More recent techniques emphasize lightweight personalization by generating stylized results from a single reference image and prompt [53], or by combining a style reference with a separate content or structured input for finer control [6]. However, these computational approaches frame style primarily as reproduction of output, ignoring the potential creative process involved when humans interact with these AI-infused systems.

This output-centric orientation can hide an artist's true intention and neglect the reflective practice that artists engage in to reassess stylistic choices. Particularly when GenAI tools impose a strong, built-in aesthetic direction, they override original expression causing the outputs of diverse users to become increasingly standardized. This loss of unique visual identity can subsequently lead to homogenization of style [4, 24, 54].

Furthermore, most digital creativity-support systems reduce style to reproducible visual features, optimized for fidelity rather than supporting artistic practice [39, 42]. Porquet et al. further critique that current style transfer tools provide little value to artists and risk diminishing their agency [51, 65]. GenAI systems often abstract away explicit prompting, translating high-level concepts into opaque intermediate representations that make it harder for artists to understand why specific images are produced, ultimately depriving artists of artistic control and agency [9].

These approaches fundamentally clash with how artists approach their work. Although recent HCI research has started to look into the integration of GenAI into artists' creative workflows, the research focus has been on ideation [12, 75, 82], generation [64, 81], or on fine-grained artistic control [55], rather than supporting artists in exploring a new style [60].

Additionally, prior work has used AI-generated feedback to facilitate reflection in creative practice [13, 23, 85, 87]. Because art-making is socially situated, feedback from peers and audiences can shape artists' decisions, motivation, and creative identity [18, 28, 47, 74]. Recent systems have simulated audience or user perspectives through personas to support creative refinement and design evaluation [17, 40, 63]. For instance, writers can specify AI personas that mirror their target readership [7]. In theater, Audience Amplified used virtual spectators to increase social presence and engagement [48]. However, these interventions primarily support reflection on a specific artifact or experience, leaving underexplored how AI-mediated reflection and simulated social perspectives may shape artists' longer-term stylistic practices.

To shift the focus from outcome-centered style reproduction toward process-centered style exploration, we proposed a process-centered framework based on interviews with professional digital artists' style exploration practices and evaluated it to understand how to scaffold stylistic exploration with GenAI while maintaining the artist's creative agency.

3 Method

Our research employed a mixed-methods approach, including semi-structured interviews, questionnaires, and log data, to comprehensively understand artists' current practices when exploring new art styles, their perspectives on involving GenAI in this process, and how our proposed AI-assisted workflow influenced their style exploration. All studies received approval from the ethical review board of the authors' institution.

The research contains three parts of studies: (1) Formative Study (RQ1), (2) Controlled Experiment Study (RQ2), and (3) Field Study (RQ3). The interview data were analyzed using thematic analysis [11]. All interviews were transcribed and summarized. Two authors conducted the initial coding, one of whom had prior professional experience as a concept designer, and the resulting themes were iteratively discussed and refined within the research team until consensus was achieved.

4 Formative Study: Artists' Style Development: Practices, Challenges, and Design Goals

4.1 Participants

We recruited 10 professional digital artists (ages 23-38; 6 male, 4 female), including 4 concept artists and 6 illustrators (with 4-15+ years of experience, mean = 9), who balance personal expression with client and viewer demands, making them well-suited for studying style development. Participants were recruited through artist community connections and personal referrals by email to request collaboration. All the participants are based in East Asia. Detailed participant information, including their participation in each study, is provided in Appendix A. Participants were compensated 25 $USD for a 1.5-hour interview study.

4.2 Study Procedure

First, we informed participants about their rights and obtained their consent to proceed with the interview. The interview was conducted via Google Meet. We asked participants to prepare examples of their personal work and project experiences beforehand, particularly focusing on their artistic style development and adjustment processes, including any artworks that could demonstrate their style development journey. Each interview lasted 1-1.5 hours.

4.3 Findings

4.3.1 Practices and Challenges in Style Development. The development of style is a complex process that requires substantial investment in time, research, deconstruction, and experimentation. It is not only an individual pursuit and exploration but is also influenced by social factors.

All artists mentioned that personal preferences drive their exploration. They began by collecting and exploring reference artworks by other artists, whether through actively searching or passively browsing. When artists find artworks they admire, they want to imitate and learn from them. As one participant explained, "*I saw that artist's style and thought it was so cool, and the way it expressed using the texture made me want to try*" (P4).

A common next step was to carefully study other artists' works and break down their techniques from styles. We identified the aspects that the artists focus on, including *composition, linework, color, lighting, rendering style, and shape language.* As one artist described, "*I will find an artwork that I like, then I will break down its color use, techniques, shapes, and everything*" (P9). This analytical process goes beyond surface imitation. Instead, it emphasized understanding the reasoning behind stylistic choices. As P6 reflected, "*I need to understand why others create that way, and what results that approach produces*". In this sense, decomposition involved not only learning the "how" but also uncovering the "why" of artistic decision-making in developing a certain style. Finally, artists engaged in experimentation and adaptation, which sometimes involved conscious self-improvement or combining their preferences and habits. As P10 shared, "*I have tried to imitate some artists' works... then integrate that into my personal drawing style.*" With repeated experimentation and considerable effort, artists incorporated these insights into their own evolving style practices.

Additionally, social factors, including feedback from clients, viewers, and peers, significantly influence both the direction of decision and the details of style development. As P10 shared, "*Fans kept saying they loved my bold, saturated color strokes, so I leaned into that and made it a big part of my own style.*" At the same time, frustrations arising from not fully meeting client expectations or resonating with viewers may also lead artists to reflect on their personal style. Advice from other professional artists could also provide essential reference points for refinement. For example, P8 notes, "*When seeing the low engagement on social media for my works, I started seeking artist friends' suggestions [for adjusting my style].*" These examples show that style development is not solely an individual process but also a social one, where artists rely on social feedback to assist them in reflecting on their stylistic choices.

4.3.2 Challenges in Using GenAI in Style Development. Interview findings showed that while some artists use AI for ideation and generating materials in their creative practices, none of our participants reported using GenAI or style transfer for style exploration.

Visually Appealing but Hard to See the Hidden Rationale. First, AI images are difficult to analyze and fail to provide the information artists need for style development. Although AI outputs may appear visually appealing, they lack the process and underlying creation logic that typically guide human artworks (P1, P4, P5, P7, P8). From a technical perspective, AI images' illogical generation creates confusion for artists to try learning styles from them. As P8 explained, "*[In AI images,] there are things you just can't make sense of, those things just confuse anyone trying to analyze it.*"

Furthermore, AI-generated images fall short in conveying deeper meanings such as the creator's intent and emotional expression, which usually stem from intentional artistic choices. Artists described style exploration as a process that involves examining both the *technical execution* and the *conceptual thinking* behind other artists' works. However, since AI images remix countless unseen sources without clear attribution or rationale, they hide the artistic intent that is critical for learning and reflection (P2, P3, P10). This diminishes the value of AI-generated images as references.

The Deprived Creative Agency. The second challenge concerns the loss of creative agency. As P1 noted, "*GenAI tends to produce complete designs that create a false sense of completeness.*" Such completeness deprives artists of opportunities for intervention, modification, or further contemplation. Furthermore, artists worry that AI-generated references can undermine their creative style development and independent thinking. As P7 admitted, "*If I check AI results while creating, my ideas get locked in too easily. I only use AI when clients have clear requests, then I can just work with that constraint. But for developing my own style, I almost never use AI.*"

These challenges explain why current AI and style transfer models do not meet artists' needs for style development. While AI may excel in certain technical aspects (e.g., generating appealing images), it falls short of supporting the deeper, more intentional processes that artists require for meaningful style development and growth.

4.4 Design Goal

Based on the findings, we identified three design goals for integrating GenAI into artists' style exploration practices.

- **DG 1: Keep Artistic Agency when Co-exploring with GenAI:** Empowering artists to reflect, critique, and steer the direction of style exploration, rather than passively consuming AI outputs.
- **DG 2: Make Style Exploration more Analytical and Explicit:** Help artists expand their interpretation of the "how" and "why" behind stylistic outputs by breaking down reference elements (technical aspect) and revealing underlying aesthetic principles (conceptual aspect).
- **DG3: Integrate Social Perspectives into Individual Style Exploration:** AI can simulate potential feedback from representative audience groups, enabling artists to reflect on how their work may be interpreted and received by others.

5 Analyze, Experiment, and Resituate: A Framework for Creative-support Tools

Building on insights from Formative Study, we present the Analyze-Experiment-Resituate (AER) framework within an AI-assisted style exploration workflow. The AER framework aims to embed creative agency and social feedback into the generative process. To examine its effectiveness, we developed a proof-of-concept system that operationalizes the AER workflow and enables empirical evaluation through user studies.

5.1 Overview of the AER Framework

The Analyze-Experiment-Resituate (AER) framework structures the AI-assisted style exploration process into three stages, addressing the design implications discovered in the formative study. This AER framework is designed to enable artists with an original-developed

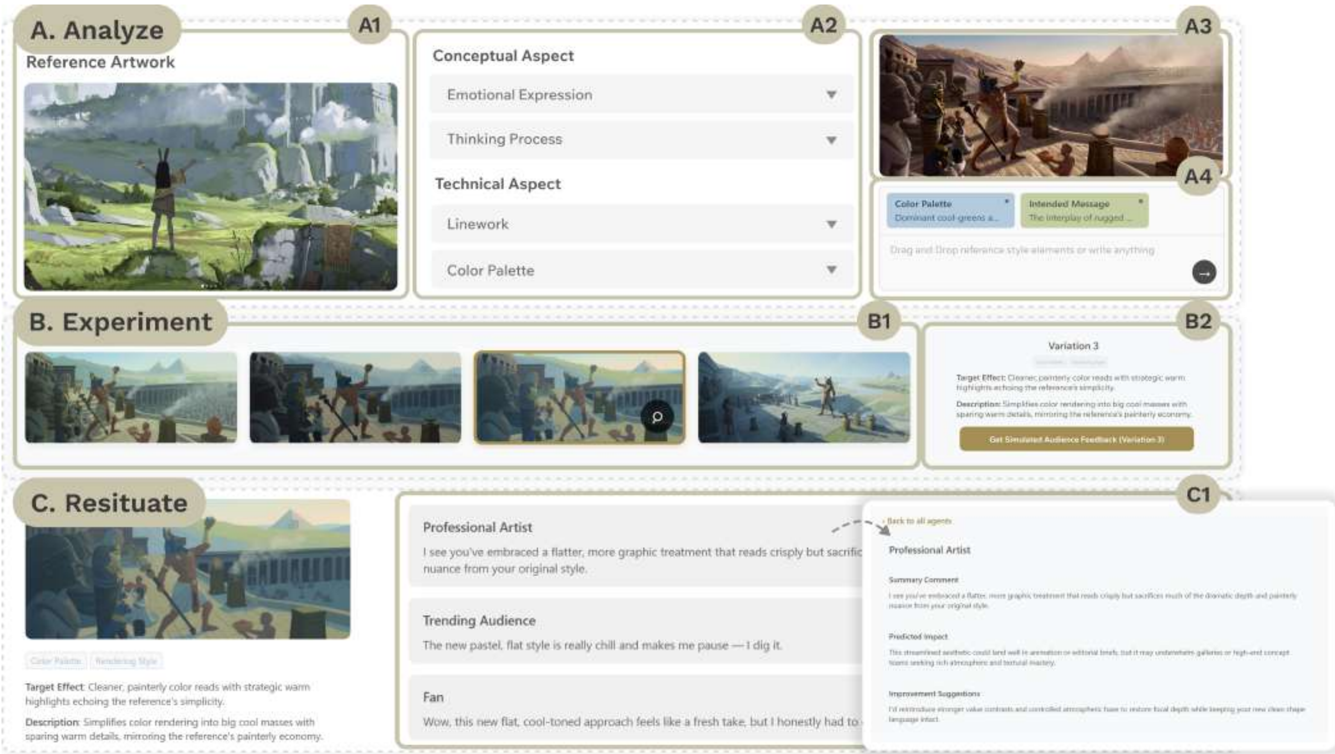

Figure 2: The AER-embedded system consists of three panels: (A) *Analyze*, which decomposes reference artwork into technical and conceptual elements; (B) *Experiment*, which generates and explains stylistic variations based on selected elements; and (C) *Resituate*, which provides simulated feedback from professional artist, trending audience, and fan perspectives.

style to explore new styles by integrating their existing style with others they wish to pursue.

5.1.1 Analyze. *Analyze* refers to the process by which GenAI breaks down the technical and conceptual elements of an artwork. Grounded in the practices identified in our formative study, where artists dissect and reason through the artworks they admire, this stage, our system extracts both technical elements (e.g. composition, shape language, linework, lighting and atmosphere, color palette and rendering style) and conceptual elements (e.g., emotional expression, cognitive process, intended messages, and artistic influences). *Analyze* stage addresses the challenge of interpretability by surfacing specific layers of an artwork rather than simply presenting a style-copied piece. This approach aims to help artists understand how a style is constructed and how stylistic choices are made. The generated analyses are designed to prompt reflection and discussion during style exploration as provisional interpretive resources.

5.1.2 Experiment. *Experiment* refers to the process by which GenAI presents various combinations for artists to experiment with different technical and conceptual elements while exploring a new style. This stage enables artists to explore stylistic variations actively, allowing them to guide the style generation using decomposed elements from reference artworks in the *Analyze* stage or their own thoughtful input. At this stage, the system allows artists to specify and choose the technical or conceptual elements they want to incorporate into their artwork. The system then generates several interpretable variations, each accompanied by detailed explanations outlining what was changed, how it was applied, and the rationale behind each direction taken. This balance between active control and diverse outputs enables artists to experiment in various directions while maintaining an understanding of the underlying stylistic logic, which is a critical challenge when using a style transfer model to directly apply one's style to another artwork. Unlike directly copying one style to another, the *Experiment* stage preserves artistic agency and encourages experimentation and authorship. Artists are not passive recipients of AI output but remain central in driving stylistic direction.

5.1.3 Resituate. *Resituate* refers to the process in which the AI-assisted tool simulates the social feedback of various social roles that artists consider in their style exploration practices. Building on the findings from the formative study, which indicate that artists depend on peer critiques and viewer reactions to adjust their styles, this *Resituate* stage presents social feedback articulated in the voices of key social roles that artists value. These roles, such as a fan, a professional artist, or a general audience, are grounded in our formative study results and supported by prior literature [19, 69]. Each feedback role shared comments, predicted impacts, and suggestions for improvement from their perspective, aiming to allow artists to preview how different viewer groups might interpret or respond to a given style artists plan to explore.

Together, these three stages show how GenAI can be integrated into professional artists' workflow of style exploration: decomposing references in the *Analyze* stage, trying out variations in the *Experiment* stage, and seeking feedback in the *Resituate* stage.

5.2 Implementing AER-embedded System

Figure 2 shows the system's user interface, and the complete interaction workflow is provided in Appendix C. To use this system, users have to upload two artworks: one that represents their current style (Fig: 2-A3) and another that serves as a reference for learning or inspiration (Fig: 2-A1). This mirrors common artistic practice, as seen in our formative study and prior literature, where stylistic elements are extracted from a reference and applied to one's own work [59]. Likewise, state-of-the-art style transfer methods typically pair a style reference with a content or structural reference [6].

5.2.1 Analyze. The system adopts GPT-5[1] as its primary multimodal large language model (MLLM). Prior studies have validated the capability of MLLMs to analyze stylistic elements in artworks [87]. The system analyzes the reference artwork through a dedicated prompt designed to identify its technical and conceptual aspects (Fig. 3-A). These components are visualized as tags in the web-based interface (Fig: 2-A2), which users can drag into the chatbox to guide subsequent generations (Fig: 2-A4). For example, under the technical aspect *Rendering Style*, the system may output: "*Painterly, with broad, confident brush masses and visible strokes that suggest texture rather than detail.*" Under conceptual aspects, it might describe: "*The sweeping vista and clear atmospheric ladder suggest openness, scale, and forward momentum. By arranging large directional planes and keeping the palette fresh and cool, the image nudges the viewer toward thoughts of exploration and possibility.*" This conceptual analysis is accompanied by three related technical tags: composition, color palette, and lighting & atmosphere.

5.2.2 Experiment. After reviewing all analyzed aspects, the participant selects an emotional expression component, tagged with the rendering style and the color palette, and an additional rendering style component as input. A Style Tweak Direction LLM then combines the selected style elements with the user prompt to generate style-tweaking directions. In parallel, a Content Description Extraction MLLM extracts content descriptions from the user's original artwork. A Style Prompt LLM subsequently integrates the style directions and extracted content descriptions to construct generation prompts (Fig. 3-B). The system generates four style tweaking directions based on these selections, and constructs dedicated prompts for stylistic-controlled image generation. We used Flux-Kontext-Pro[2] as the image generation model for its ability to integrate features from two images into one output. Each prompt combines the content of the original user image with a style modification instruction, ensuring that only the intended changes are applied while preserving other content. Each variation is paired with a textual explanation (Fig: 2-B1, B2). In this example, the first variation aimed to "*create cleaner, painterly color reads with strategic warm highlights echoing the reference's simplicity*", modifying the *color palette* and *rendering style*. The style change is explained as: "*Simplifies color rendering into big cool masses with sparing warm details, mirroring the reference's painterly economy.*"

5.2.3 Resituate. Once the user identifies an image of interest, they click "Get Simulated Audience Feedback" to receive responses from the three aforementioned viewer roles. We use AutoGen [83] as the framework for generating agent feedback, with system prompts specifying the characteristics of the role (Fig. 3-C). The simulated professional artist focused on sharing constructive critique, the simulated trending audience on immediate social-media appeal, and the simulated fan on stylistic consistency and recognizability. The interface first displays summary comments from each agent (Fig: 2-C1). For instance, the professional artist might respond: "*I see you've embraced a flatter, more graphic treatment that reads crisply but sacrifices much of the dramatic depth and painterly nuance from your original style.*" Users can then select a specific agent's feedback to review more detailed outputs, including predicted impact: "*This streamlined aesthetic could land well in animation or editorial briefs, but it may underwhelm galleries or high-end concept teams seeking rich atmosphere and textural mastery*", and improvement suggestions such as "*I'd reintroduce stronger value contrasts and controlled atmospheric haze to restore focal depth while keeping your new clean shape language intact.*" Then, after viewing the feedback, the user can type into the chatbox to begin a new round of exploration.

6 Controlled Experiment Study: Exploring and Evaluating AER Framework

We conducted a within-subject study with 16 professional digital artists to answer: **(RQ2) How does the proposed AER framework influence artists' agency and reflection during style exploration?**

6.1 Experiment Design

We compared the proposed AER-embedded system with a direct style transfer baseline, as it is one of the AI-assisted tools most closely associated with stylistic creativity and has been widely used in both research and practice as a means of "copy styles" [65]. We implemented the baseline with a similar interface to reflect common direct style transfer workflows.

The core interaction of the non-AER-embedded (direct style transfer) system was adapted from MidJourney[3], a widely used GenAI service. It included (1) uploading style reference artworks, (2) uploading personal artworks as content references, (3) a text input area for prompting, and (4) a section showing generated results. The backend used Flux-Kontext-Pro, the same image generation model as the AER-embedded system. It also utilized the same prompt structure that merged content descriptions from the user's artwork with style descriptions from the reference artwork. The user's prompt guided how these style elements were integrated, producing outputs that reflected this combination. The interface of the non-AER-embedded system is shown in Appendix C.

During the study, participants used both systems to explore new styles with two types of artworks prepared in advance: (1) their own works or projects representing their current style, and (2) reference

[1]GPT-5, https://platform.openai.com/docs/models/gpt-5
[2]Flux-Kontext-Pro, https://bfl.ai/models/flux-kontext
[3]MidJourney, https://www.midjourney.com/home

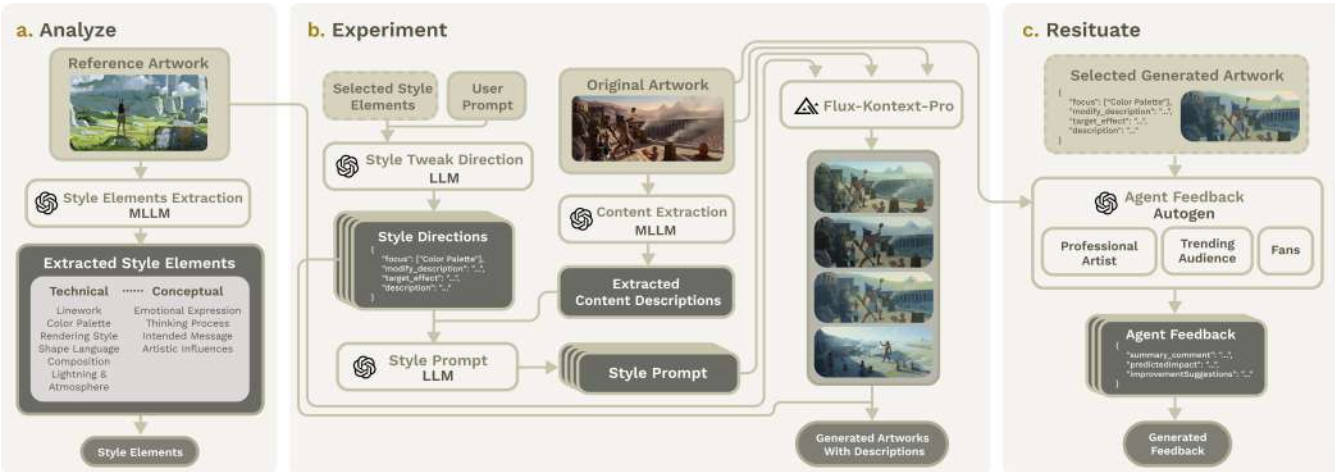

Figure 3: The system diagram for AER-embedded system.

artworks they admired and wished to explore stylistically. The order of conditions was counterbalanced across participants. In both conditions, participants were asked to explore potential stylistic directions, with the resulting outputs serving as inspirational references rather than final artworks. Participants were also encouraged to think aloud when using the system. Outcomes could include AI-simulated illustrations, insights gained during exploration, and possible next steps for their style development.

6.2 Participants

We recruited 16 professional digital artists (age 23-38; 9 male, 7 female), including 6 concept artists and 10 illustrators (4-15 years of experience, mean = 7.25). Seven participants (P1, P2, P3, P4, P5, P7, P9) had participated in the Formative Study and were re-invited via email. The remaining participants were recruited using the same approach as we did in the Formative Study. All participants received 35 $USD compensation for a 2-hour study.

6.3 Procedure

The study began with a 10-minute briefing. Participants were informed about the study purpose, their rights, and provided consent before proceeding. For each condition, the session included a 10-minute tutorial, 30-40 minutes of style exploration, and a 5-minute post-task questionnaire after participants used each system. The study concluded with a 30-minute semi-structured interview.

6.4 Measurement

(1) **Self-reported Post-task Questionnaire**: Participants completed three validated questionnaires: Agency [78], Creative Self-Efficacy [14], and Technology-Supported Reflection Inventory (TSRI) [8]. All items were rated on a 7-point Likert scale (1: Strongly Disagree, 7: Strongly Agree). We adapted the items to reflect style exploration; for instance, "*I am in full control of the style decisions I make using this approach.*" All scales demonstrated high internal consistency: Agency (α = .86), Creative Self-Efficacy (α = .90), and TSRI (α = .91), including its sub-constructs of Insight (α = .86), Exploration (α = .82), and Comparison (α = .78). Detailed items are provided in Appendix B. After confirming normality via Shapiro-Wilk tests, we analyzed the data using paired t-tests and calculated Cohen's d for effect sizes.

(2) **Semi-Structured Interview**: We conducted in-depth semi-structured interviews to triangulate the quantitative results and examine how artists engaged with the AER-embedded system compared to direct style transfer. We focused on understanding participants' agency, creative process, sense of future direction in style development, and perspectives on AI-assisted approaches while using two systems.

6.5 Findings

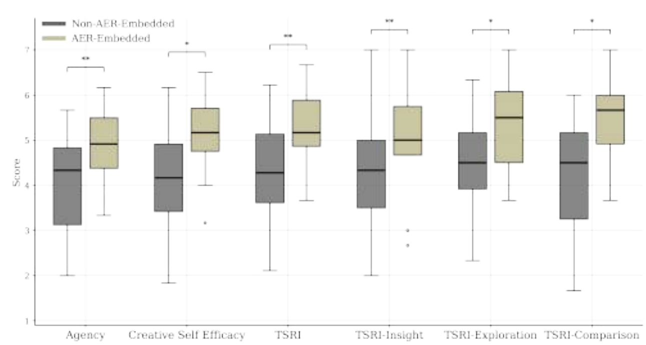

Figure 4: Questionnaire results from the within-subject task. Participants rated Agency, Creative Self-Efficacy, and the Technology-Supported Reflection Inventory (TSRI), TSRI-Insight, TSRI-Exploration, TSRI-Comparison for both the Non-AER-Embedded and AER-Embedded system using a 7-point Likert. scale. *: p < .05 and **: p < .01.

6.5.1 *AER-embedded System Increased Artists' Agency.*

Agency in this context refers to the sense of truly driving the direction and outcome of style exploration. Result of the Paired-T test showed that participants using the AER-embedded system reported significantly higher perceived agency compared to the direct style transfer (Figure 4; $t[15] = -2.948, p = .010, d = 0.853$, mean difference = 0.875). Qualitative analysis of the interview further revealed three main reasons underlying this enhanced sense of agency, with many explicitly attributing their experience to the *Analyze* and *Experiment* mechanisms.

Traceability. Artists emphasized that agency is grounded in whether they could clearly see how their decisions influenced the output and whether the reasoning behind those decisions was traceable. P5 described, "*After selecting analyzed elements, I can see how my choices change the results, and the side-by-side display of tweaking directions helps me better understand what I'm referencing.*" In contrast, the outputs from the non-AER-embedded system often felt opaque. As P14 noted, "*[When looking at the output from the Non-AER-embedded system] I don't know how it adopted the artworks or what elements it actually used.*"

Controllability. By making choices from analyzed elements in the AER-embedded system, artists felt they were creating rather than receiving what AI had determined for them. As P11 reflected, "*This felt like I was truly creating, because I was making choices.*" While most artists favored the AER-embedded framework, a few found a different form of control in direct style transfer. For P16, the agency resides in the "*deliberate process of formulating the prompt*". While P16 acknowledged that AER allows better guidance of the creative direction afterward, the artist viewed the initial act of defining the prompt as also the expression of agency.

Alignment with Artistic Identity. The sense of agency was further supported when artists felt the AER framework aligned closely with their artistic identity. Participants described AER as a partner that supports deeper exploration and reflection, often likening the experience to conversing with someone who truly understands art. For example, P1 noted that its analysis "*spoke his language*", lowering his guard, while P9 described it as "*like chatting with another artist*" with clear and familiar logic.

6.5.2 ***AER-embedded System Increased Reflection and Confidence in Future Style Development*.** Participants using the AER-embedded system reported significantly higher levels of self-efficacy (Figure 4; $t[15] = -2.9, p = .011, d = 0.88$, mean difference = 1.00) and technology-supported reflection (TSRI) (Figure 4; $t[15] = -3.21, p = .006, d = 0.92$, mean difference = 0.96) compared to the non-AER-embedded style transfer. A closer look at the TSRI sub-scales revealed that AER framework strengthened artists' ability to gather *Insight* ($t[15] = -3.54, p = .003, d = 0.67$, mean difference = 0.85), to engage in *Exploration* of style possibilities ($t[15] = -2.50, p = .025, d = 0.78$, mean difference = 0.90), and to draw *Comparisons* in a social sense ($t[15] = -2.71, p = .016, d = 0.97$, mean difference = 1.13).

Interview results showed that *Analyze* helped artists interpret the meaning of references and identify stylistic elements they had not previously articulated. P5 reflected, "*I realized I liked the high contrast and vector-like color blocks. In the future, I can search for more styles based on this keyword.*" It also sparked new directions for exploration: "*It's like an extra spark from of interpretation... opening up more possible directions [for style exploration]*"(P19). While interacting with the stylistic elements in the *Experiment* stage, artists further described the generated images as practical references that helped them clarify direction and anticipate challenges when trying out a style. As P11 noted, "*[It] helps me realize what problems I might run into, or when the result may not turn out as good as I imagined. That saves me from wasting time going down the wrong path.*"

In the *Resituate* stage, many valued the feedback generated by the professional artist agent for its constructive insights, while the fan agent helped highlight their distinctive traits and what might be lost when shifting styles. For example, P14 shared, "*It pointed out that my work was missing particle effects, something I usually include. That reminded me how to reintroduce my own style into the concept art so it truly feels like my own.*" Feedback from trending viewers was often considered less insightful, frequently compared to "*passerby comments*" (P13), though some still saw its value in commercial contexts, as P16 noticed that the artwork has to be rich and memorable enough for general viewers to notice.

In contrast to AER, the baseline framed style exploration primarily as prompt iteration rather than explicit interpretation or reflection on style. Most artists did not begin by interpreting references (P1, P5, P7, P13, P14, P16, P19), but instead started with simple prompts such as "*use this style to generate the artwork*" and refined subsequent prompts based on what was missing from the outputs. As a result, artists relied mainly on their own aesthetic judgment to extract usable fragments from the generated images and synthesize them into a coherent direction for exploration.

6.5.3 Challenges and Opportunities in AER-embedded Workflow.

Being Constrained in the Fixed Workflow. Artists selectively emphasized different steps depending on their goals, preferences, and stage of style exploration. For some (P2, P3, P11), they stated that *Analyze* alone already provided substantial inspiration. As P2 explained, "*The analysis is powerful. Once I understand the logic, I don't even need it to generate simulated artworks, because I'm an artist, I can learn from it, and I have the skills to make the art.*" Also, A few (P4, P18) often skipped the *Resituate* stage. As P18 explained, "*Until I actually draw it myself, it's a completely different matter, so I don't need feedback on a work that isn't mine.*" This suggests the need to enable professional artists a flexible workflow to work with creativity support tools during style exploration.

AER Framework Resembles Artists' Daily Practices. Many participants emphasized that the AER framework felt closely aligned with their everyday practices of style exploration and learning. P1 described its versatility across different stages of professional work: "*With [AER], I can see myself using it during the ideation phase, when I'm preparing to pitch to clients, or even after completing a project if I want further to explore style variations. It feels much more integrated with my actual [creativity] workflow.*" P13 similarly compared the workflow to the teaching and analysis process: "*This [AER workflow] is very close to how I teach students, telling them how to look at the atmosphere, composition, and techniques.*"

Thus, these findings motivated us to explore the long-term impact of AER framework on style exploration for professional artists.

7 Field Study

While the controlled experiment examined the immediate effects of AER on artists' agency and reflection, style exploration is rarely a one-session activity. To understand how AER fits into ongoing creative practice, we conducted a two-week field study with four professional digital artists. We asked: **how do artists engage with the AER framework over time during style exploration?**

7.1 Participants and Procedure

We recruited four professional artists who had participated in both our formative and controlled studies: two environment concept artists, P2 (24 years old, 6 years of experience) and P4 (27 years old, 4 years of experience), and two illustrators, P1 (31 years old, 10 years of experience) and P3 (30 years old, 10 years of experience), both of whom specialized in character illustration with rich environments. Each participant received approximately $220 USD.

For the field study, we deployed AER as a web-based system for two weeks. We instructed participants to use it for about one hour (a session) per day. While daily use was encouraged, it was not strictly enforced. Participants could skip one or two days and make up their usage later, providing flexibility while ensuring sustained engagement with the system. We updated the system to use Flux 2 Pro[4], which provided finer stylistic recombination, and added support for replacing the image at any stage of the AER workflow with either a generated or user-uploaded image. We did not assign a fixed task for them to use the system, allowing participants to appropriate any feature of the Analyze, Experiment, and Resituate stages according to their own creative goals.

After each daily session, participants completed a short diary entry describing how they used the system, any notable discoveries, and satisfying experimentation. At the end of the study, we conducted a semi-structured interview with each participant to reflect on their usage over time. The interviews also drew on participants' diary entries, prompting them to revisit and elaborate on specific experiences and patterns documented across the study.

7.2 Findings

Our field study shows how professional artists integrated AER into creative practice over time, how their use evolved, and what this implies for AI tools for artistic exploration. Figure 5 illustrates each participant's proportional usage across three stages, with a mean total usage time of 9.63 hours. On average, participants spent the most time in the *Experiment* stage (64.78 %), followed by *Analyze* (25.85 %) and *Evaluate* (9.37 %). The stages were not used in a strictly linear manner; artists moved between them based on their exploration needs.

7.2.1 *How AER Influenced Reflection during Style Exploration.*

Across participants, AER supported ongoing reflection on stylistic choices, with the three stages contributing differently.

Analyze. Participants described *Analyze* as helping them externalize tacit stylistic judgments. Rather than introducing entirely new ideas, it helped them revisit previously learned principles, notice overlooked details, and clarify what they valued in a reference image they uploaded to the system. For P3, *Analyze* surfaced aspects they might otherwise ignore in a habitual workflow: "*My drawing workflow is already quite fixed, and this stage [Analyze] reminded me that there were still other elements I could pay attention to.*" Similarly, P2 felt that: "*Turning some abstract concepts into text made them more inspectable.*" *Analyze* also helped participants refine their interpretation of references. For example, after reading the stylistic elements in *Analyze*, P1 reflected: "*In this image, I initially thought what I liked was the linework, especially the hatching, but later I realized it was actually the rendering style—the way shading was expressed through lines.*"

However, some participants felt that the current labels (e.g., Composition) provided by *Analyze* were insufficient. For example, P4 felt the system's analysis often identified visible elements without explaining why they worked in context: "*while the system could label features such as S-shaped composition or visual guidance, it did not explain how those elements were arranged appropriately to create balance and emphasis within the image.*"

Experiment. Experiment stage enabled artists' reflection by making alternative stylistic directions concrete and comparable. By trying different combinations, participants examined how stylistic choices affected mood, composition, and rendering, and in turn reflected on the limits of their prior habits. For example, P4 found that experimenting with lighting revealed what had been missing from their earlier work (Fig. 6-d): "*Seeing these results with more dramatic lighting and stronger contrast made me pay more attention to thinking about how to add those elements in the future.*" P2 similarly reflected that repeated experimentation revealed the narrowness of their earlier style: "*After trying so many results, I realized my past style had been relatively consistent.*" This process also increased artists' confidence in pursuing unfamiliar stylistic directions. For example, P1, who had been working on a series of artworks around a theme, reflected that "*I used to think this series had to stay in one fixed style, but after using the system I realized it could also work very well in a different style.*" He further explained that making stylistic possibilities more concrete gave him more confidence in imagining how a new style might look, which made him "*willing to experiment more boldly*" in ways he had not found through Pinterest (Fig. 6-a).

At the same time, *Experiment* helped participants reflect on why certain stylistic elements failed when applied to their own work. P2 observed that poor results from Experiment often stemmed from mismatches in the underlying spatial and visual logic (Fig. 6-b): "*Some compositional and rendering choices only worked well because they were developed together as a whole.*" Rather than treating stylistic elements as independently transferable, seeing the unsatisfying

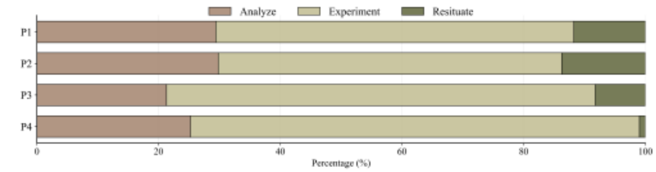

Figure 5: The proportion of usage across the Analyze, Experiment, and Resituate stages during the field study.

[4]Flux 2 Pro, https://bfl.ai/models/flux-2

results in the *Experiment* stage helped participants recognize conflicts between the reference, their own image, and the ways different stylistic elements interacted.

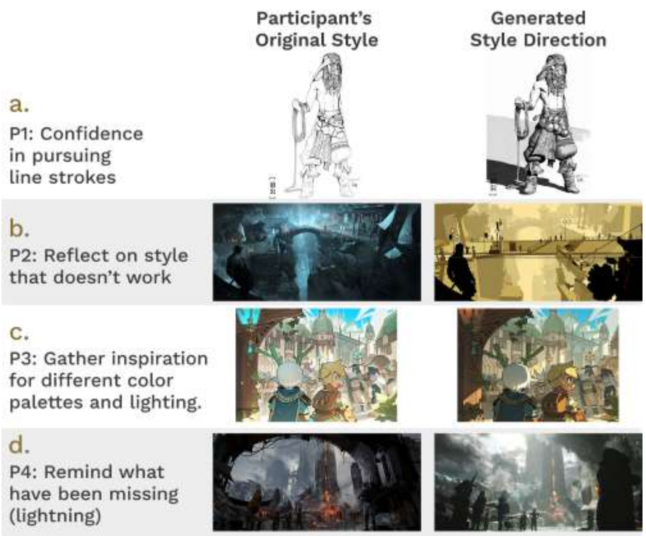

Figure 6: Examples illustrating how the Experiment stage triggers diverse forms of reflection. This stage helps artists (a) gain confidence to pursue unfamiliar stylistic directions, (b) reflect on why certain styles fail, (c) gather inspiration, and (d) identify missing elements in prior work.

Resituate. Participants' experiences with *Resituate* were more mixed. For some participants, it encouraged critical comparison between the simulated feedback from the system and their own. As P2 explained, "*I wanted to see whether it thought the same as I did,*" and even disagreement with the simulated feedback could "*prompt reflection on why the system produced a different reading*". However, most participants used Resituate less often because they were unsure about the reference value of its simulated perspectives. P4 questioned "*from what perspective the AI was looking at the image,*" while P3 said they would trust it more if it were grounded in actual audience data. Participant further noted that Resituate tended to assess images as if they were completed works, which limited its usefulness during exploration. P2 noted: "*rough outputs could still contain promising ideas, and the system's feedback would be more useful if it could identify unrealized potential and suggest how an unfinished work might be developed further.*"

7.2.2 From Style Replication to Style Exploration. This exploratory shift broadened how participants used references. Rather than copying surface appearance, they began using the system to reinterpret references more structurally. P2 noted that it was "*not just copying the visual surface, but could also reshape scene elements and proportions,*" making it "*a more innovative and interesting way for artistic exploration.*" P3 similarly extended this exploratory use beyond artwork references by experimenting with photographs, explaining that "*carefully staged photographs could produce a stronger mood,*" making them useful not as literal models to copy, but as evocative inputs for exploration.

Figure 7: More examples from the Experiment stage.

7.2.3 AER Outputs Became Parts of the Emerging Style. Participants often treated the generated images as reusable stylistic material: repositories of elements, solutions, and cues that could be carried into later work. For example, P2 described using the system after establishing a rough composition or sketch, then exploring different stylistic directions to extract "style elements" for further development rather than committing to a single generated result. Participants also integrated AER into their wider set of reference practices. P4 described combining two images to "collide" different possibilities: one might provide the desired style or lighting, while another was closer to the intended content, such as a photo or natural scene. This helped them identify reusable details that they might not have discovered through manual exploration alone. P3 similarly suggested that, over time, they might incorporate AER into everyday Pinterest browsing by uploading images for textual analysis, rather than using it for an immediate task.

8 Discussion

8.1 Shaping Stylistic Trajectories with AER

8.1.1 Reclaiming Agency through Process. Many artists remain hesitant to adopt GenAI tools due to limited interpretability and control [41, 45, 49]. Our findings in Controlled Experiment Study with direct style transfer echo this similar concern. Participants described crafting prompts and then "*waiting for whatever it [GenAI] wants to show me*" (P13), which highlights the unpredictability inherent in the image generation process. AER framework addresses these limitations by embedding interpretability and control into the workflow. *Analyze* breaks reference artworks into stylistic elements grounded in domain knowledge, making analysis explicit and actionable while supporting more precise expression of intent. *Experiment* generates style variations through a two-stage process: first, defining a style direction (what and why), then specifying how to realize it. Unlike prior systems that map text directly to generated visual outputs [15, 25, 81], AER foregrounds the intentionality behind stylistic shifts, an aspect our Formative Study identified as important to style exploration. *Resituate* introduces multi-perspective feedback that broadens creative possibilities and supports reflection and further iteration, consistent with prior work on the value of diverse perspectives for creativity [35, 73].

8.1.2 Supporting Reflections on the Long-Term. During the field study, we observed that artists engaged in *reflection-in-action* while interacting with the AER framework, continuously shaping their style exploration. As a process-oriented framework, AER supports ongoing thinking, decision-making, and exploration throughout the creative workflow. We further observed a shift in artists' mindset: from *style replication* toward *style exploration*. While prior work suggests that excessive reliance on AI can reduce creativity [21], our findings indicate that AER instead promotes exploratory thinking and experimentation when artists work with GenAI systems, which may enhance stylistic diversity in the long run. This is particularly important given growing concerns that GenAI systems can lead to aesthetic homogenization [21, 51]. Viewed through the lens of reflective creative support tools' design patterns [50], AER supports reflection by inferring artists' stylistic intent in *Analyze* and providing interpretive refraction in *Resituate*. These interactions encourage artists to question assumptions, justify decisions, and reflect more deeply on their stylistic goals.

8.2 Integrating AER Framework into the AI-assisted Creative Process

Artists did not treat AER workflow as strictly linear; instead, they flexibly adapted stages to fit their own practices. In the controlled experiment study, several participants also noted the potential of applying *Analyze* to their own prior artworks as a source of inspiration. This suggests that the AER framework positions artists as the primary drivers of the creative process.

This also highlights an important characteristic of our participants, professional artists, whose expertise is particularly valuable for understanding how GenAI can support creative practice. Their experience enabled them to prioritize stylistically relevant information when co-exploring style with GenAI.

At the same time, system-driven analysis in the *Analyze* stage raises concerns. While automated analysis can surface stylistic elements that artists might otherwise overlook, it can potentially make humans gradually offload this important analytical ability to AI-assisted creativity-support tools. Prior work cautions that overreliance on AI can hinder skill development [57], highlighting the need to balance automation with opportunities for interpretive reasoning [77]. We encourage future work to further examine how system-driven decomposition influences the creative process, as well as how GenAI can be designed to support artists with varying levels of expertise, particularly novice artists.

AER framework contains artists' actual practices for style exploration, including studying references, experimenting, and seeking feedback. We expect this three-part pattern could be extended to other art domains: For example, in music, musicians analyze influences (analyze), test motifs (experiment), and share drafts for critique (resituate) [27, 36]. Similar structures appear in writing [22, 72], product design [10], and other creative fields. Rather than collapsing reasoning into end-to-end automation, creativity-support systems should be structured around interpretable elements, user-driven recombination, and embedded reflection. Viewed this way, AER-embedded GenAI shifts from an automation tool to an infrastructure that scaffolds exploration and creative growth. We encourage further research to examine this AER framework for influencing style exploration in fields beyond digital arts.

8.3 Reflection and Future Work

Unlike prior work that emphasizes efficiency or output quality in AI-assisted creative works, our approach focuses on designing a GenAI workflow that aligns with artists' practice, distinguishing it from reproduction tools in the creative supply chain [65]. However, our implementation allows users to reference other artists' works and generate images in their style, often without consent [58, 65]. AER may also further encourage such referencing through style transfer models. Drawing inspiration from other artists is a common practice in the art world. While AER aims to help artists find inspiration effectively through referencing and analyzing, we acknowledge that using GenAI can raise ethical concerns. These include issues related to style mimicry, copyright risks, and misattribution [70]. Prior work highlights how creative practices are supported within broader ecosystems [3]. Building on this perspective, we call for future research to explore how GenAI systems can better embed mechanisms for attribution, consent, and credit, ensuring that artistic contributions are recognized and sustained.

Additionally, in our *Analyze* implementation, we use MLLMs to analyze artworks and evaluate their interactional usefulness, as artists can inspect, challenge, and selectively incorporate the outputs during style exploration. However, analyses derived solely from visual features may still produce context-insensitive interpretations. Artistic style is shaped by cultural influences, historical movements, and dialogues with preceding artists [20]. In our formative study, participants expressed a desire to understand the artists, movements, and influences behind artworks. Such provenance is often absent from current GenAI systems. Future AER-based systems could address this limitation by allowing artists to annotate references with cultural, historical, or biographical context and by incorporating retrieval-augmented models grounded in such information. This direction aligns with emerging HCI work on relationship-aware art exploration [2]. Future validation could compare generated analyses against expert artist annotations and assess whether the outputs are both plausible and contextually grounded.

Furthermore, while the *Resituate* stage introduces simulated social roles to diversify artists' perspectives, our findings revealed a tension regarding the transparency and focus of AI-generated feedback. Users noted that their lack of understanding of AI evaluation mechanisms and logic led to psychological resistance to feedback (Section 7.2.1). Future work could explore different methods to explain the relationships between AI-generated feedback and specific stylistic elements. We also acknowledge that including a "trending audience" persona is a value-laden design choice that should be implemented with caution. It was introduced to reflect pressures artists already reported in our formative study, rather than to prescribe platform visibility as a goal. The three personas (professional artist, trending audience, and fan) were derived from our formative study and represent viewpoints artists in our study commonly encounter in practice. Importantly, *Resituate* is intended to provide perspectives for reflection, not to simulate actual audience reception or replace human peer feedback. Consistent with our findings, artists selectively adopted feedback based on their own goals and judgment; future implementations should provide greater control over persona characteristics. Looking ahead, building on previous research like Proxona [17], future iterations of the AER framework could integrate artists' social media metrics and historical audience data. Grounding AI feedback in authentic data could transform generic suggestions into more trusted and personalized insights.

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A Appendix A: Participants Demographic

ID	Age	Identity	YoE	AI-assisted creations / week	Gen-AI tools used	Formative Study	Controlled Experiment Study	Field Study
1	31	Illustrator	10	≈0	–	✓	✓	✓
2	24	Concept Artist	6	10	Midjourney, StableDiffusion, Leonardo, Gemini	✓	✓	✓
3	30	Illustrator	10	< 1	ChatGPT(DALL-E), Gemini	✓	✓	✓
4	27	Concept Artist	4	1	Midjourney, StableDiffusion, FLUX, Gemini	✓	✓	✓
5	23	Illustrator	5	3–4	Midjourney; ChatGPT (DALL·E); Leonardo	✓	✓	
6	33	Illustrator	8	≈0	–	✓		
7	24	Concept Artist	6	1	ChatGPT (DALL·E); Gemini	✓	✓	
8	30	Illustrator	14	≈0	–	✓		
9	38	Concept Artist	12	< 1	Midjourney	✓	✓	
10	28	Illustrator	15+	≈0	–	✓		
11	36	Illustrator	10	≈0	–		✓	
12	34	Concept Artist	5	3	Midjourney; ChatGPT (DALL·E); Gemini; Lovart		✓	
13	25	Illustrator	8	≈0	–		✓	
14	24	Illustrator	5	1	Midjourney; ChatGPT (DALL·E)		✓	
15	30	Illustrator	7	≈0	–		✓	
16	24	Illustrator	5	2	ChatGPT (DALL·E)		✓	
17	24	Illustrator	5	2	Midjourney; Stable Diffusion; ChatGPT (DALL·E)		✓	
18	32	Illustrator	15	2–3	ChatGPT (DALL·E)		✓	
19	23	Illustrator	5	≈0	–		✓	

Table 1: Demographic Details of Participants Including Age, Identity, GenAI Tools, and Study Participation

B Appendix B: Questionnaire for Controlled Experiment Study

Style Development Agency Scale
- I am in full control of the style decisions I make using this approach.
- I am the author of my creative choices when exploring styles with this approach.
- My style exploration is guided by my creative intentions when using this approach.
- The decision of which style directions to pursue is entirely within my hands when using this approach.
- My style exploration process is planned and directed by me from beginning to end when using this approach.
- I am completely responsible for the style outcomes that result from my creative decisions using this approach.

Reference: Sense of Positive Agency (SoPA) - Frontiers in Psychology

Style Exploration Self-Efficacy (During System Use)
- I will be able to achieve most of the style exploration goals that I have set for myself using this approach.
- When facing difficult style exploration tasks, I am certain that I will accomplish them with this approach.
- In general, I think that I can obtain the style insights that are important to me through this approach.
- I believe I can succeed at exploring any style direction I set my mind to using this approach.
- I will be able to successfully overcome many style exploration challenges with this approach.
- I am confident that I can explore different style elements effectively using this approach.

Reference: Chen, G., Gully, S.M., & Eden, D. (2001). Validation of a New General Self-Efficacy Scale.

TSRI: Technology-Supported Reflection Inventory
Insight
- Using the approach has been a wake-up call to make changes in my style exploration process.
- As a result of using the approach, I have changed how I approach style exploration.
- Using the approach gives me ideas on how to overcome challenges in developing my style.

Exploration
- I enjoy exploring my style development possibilities with the approach.
- The approach makes it easy to get an overview of my current style direction.

- The approach makes it easy to review my past style experiments and progress.

Comparison
- I will reflect on my style exploration results in the system with other artists.
- The approach helps me discuss my style exploration process with others.
- The system makes me think about how my style exploration compares with that of other artists.

Reference: The Development and Validation of the Technology-Supported Reflection Inventory. CHI 2021.

C Appendix C: Figures

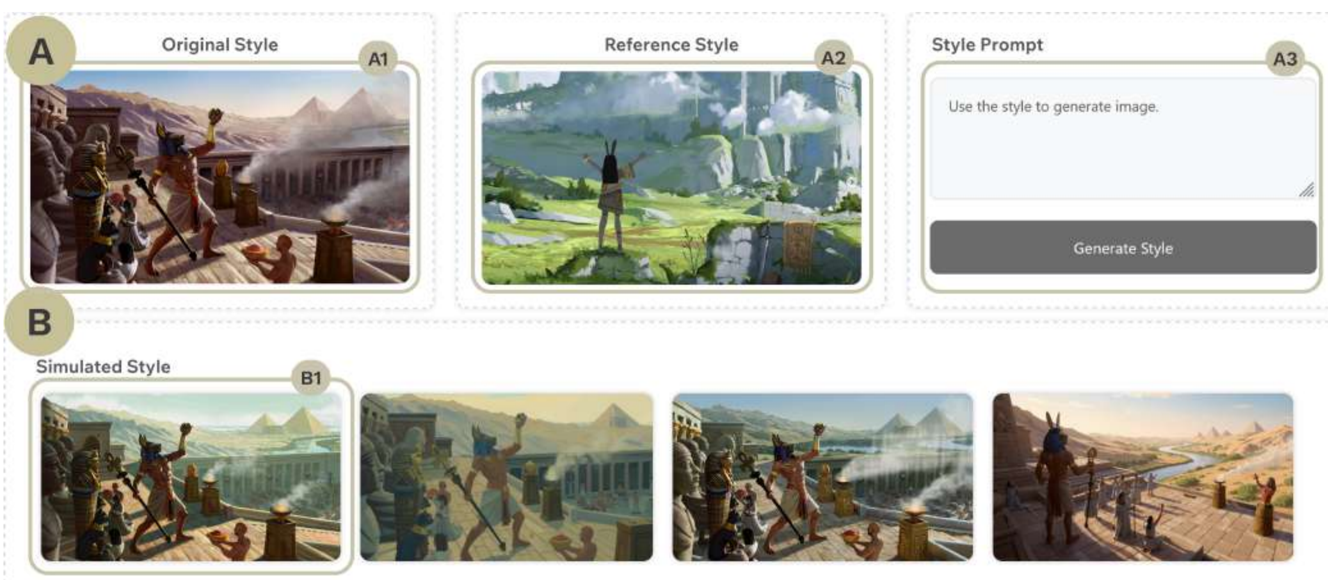

Figure 8: The UI for the non-AER-embedded (direct style transfer) system. (A) Users upload an original personal artwork (A1), a reference artwork (A2) for style reference, and input prompt in the chatbox area (A3). (B) The style simulation section displays 4 style-tweaking artworks merging the content of the user's artwork with the style of the reference artwork, which users can select (B1).

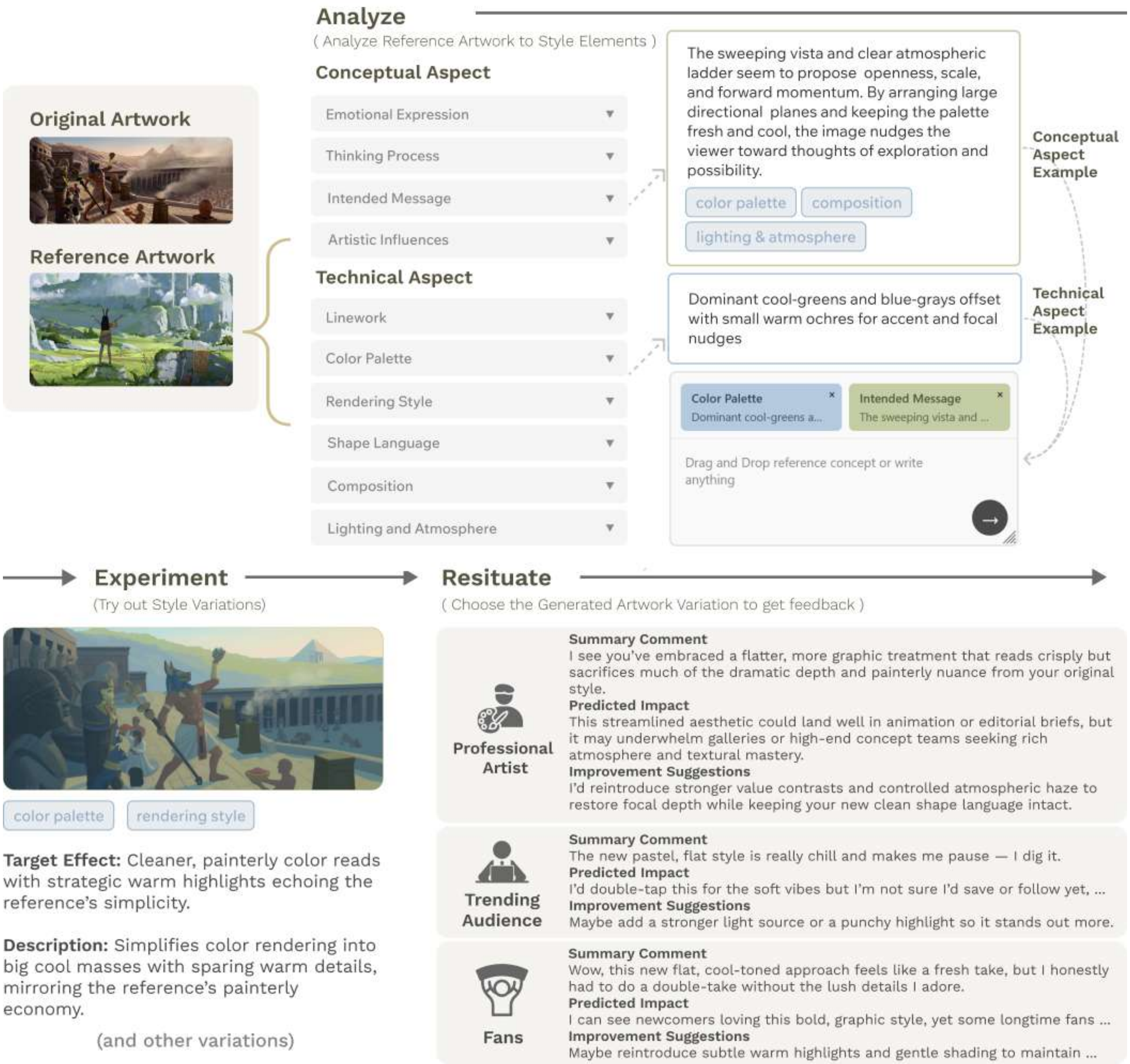

Figure 9: AER workflow. Participants were asked to explore new styles. The AER workflow analyzes the referenced artwork into conceptual aspects, converting the intended message behind the image, and the technical aspects. AER workflow generates image variations based on the decomposed element and produces the text explanations. Then, the workflow simulates three social roles and generates feedback for the selected image variation.