

CREA: A Collaborative Multi-Agent Framework for Creative Content Generation with Diffusion Models

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<https://crea-diffusion.github.io>

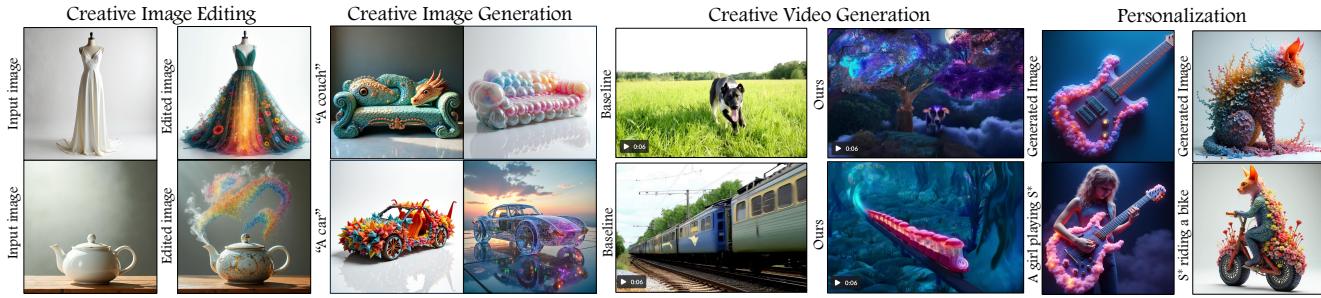


Figure 1. We introduce CREA, an agentic framework that emulates the human creative process for creative image editing and generation. Our approach is driven by collaborative interactions between specialized agents, such as a *Creative Director* and an *Art Critic*, who communicate to refine and enhance creative output. Moreover, our approach can be extended to video domain for creative video generation. Our framework can also be integrated with personalization techniques to further enrich and expand creative workflows.

Abstract

Creativity in AI imagery remains a fundamental challenge, requiring not only the generation of visually compelling content but also the capacity to add novel, expressive, and artistically rich transformations to images. Unlike conventional editing tasks that rely on direct prompt-based modifications, creative image editing demands an autonomous, iterative approach that balances originality, coherence, and artistic intent. To address this, we introduce CREA, a novel multi-agent collaborative framework that mimics the human creative process. Our framework leverages a team of specialized AI agents who dynamically collaborate to conceptualize, generate, critique, and enhance images. Through extensive qualitative and quantitative evaluations, we demonstrate that CREA significantly outperforms state-of-the-art methods in diversity, semantic alignment, and creative transformation. By structuring creativity as a dynamic, agentic process, CREA redefines the intersection of AI and art, paving the way for autonomous AI-driven artistic exploration, generative design, and human-AI co-creation. To the best of our knowledge, this is the first work

to introduce the task of creative editing.

1. Introduction

Generative AI has significantly transformed the field of image generation, producing high-quality visuals with remarkable detail and realism. Advances in diffusion models [14, 57], GANs [31], and retrieval-augmented techniques [4, 65] have enabled powerful capabilities in content synthesis, making AI-driven image creation an essential tool for artists, designers, and various creative industries. These models have been widely applied in diverse tasks, including image-to-image translation [29, 52, 63], inpainting [30, 42, 57], style transfer [20, 32, 58, 79], and content-aware editing [6, 7, 11, 46], and opening up new frontiers in digital art, advertising, and entertainment, revolutionizing creative workflows.

Despite these advancements, achieving creative and artistically rich compositions still demands significant user effort. Traditional generative approaches primarily follow a prompt-to-image paradigm, where models synthesize high-quality visuals based on textual descriptions. However, these outputs often lack originality and artistic depth, as

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the models are trained to replicate patterns from their training data rather than generate novel content. As a result, users must engage in tedious prompt refinements, fine-tune model parameters, or manually edit outputs to infuse genuine creativity. This heavy reliance on user expertise and intervention limits the accessibility of generative AI as an autonomous creative assistant, placing the responsibility for creativity more on the user than on the system itself.

To address this limitation, we propose the task of creative image editing, where the goal is to modify images in a way that enhances their creative and artistic qualities with minimal user intervention. Unlike conventional editing tasks that focus on making explicit, text-driven modifications, creative editing aims to transform images into novel, aesthetically rich compositions in a disentangled way. Our approach mimics the complex process of creative image generation and editing as a collaborative team effort, drawing inspiration from human workflows where specialists iteratively refine ideas to achieve a shared artistic vision. To achieve this, we introduce a novel collaborative multi-agent framework, where agents, each with a distinct role such as *Creative Director* or *Art Critic* work in synergy to conceptualize, generate and refine creative outputs by grounding them in well-established creativity principles distilled from research from distinguished creativity researchers as shown in Table 4. This structured yet flexible approach enables the disentangled creation of highly diverse and imaginative images, ensuring both novelty and coherence at every stage of the generation process. Since creativity is a complicated task to assess and evaluate, our agents leverage the extensive knowledge in multimodal LLMs [51] based on state-of-the-art creativity principles inspired by previous work [1, 3, 5, 16, 23, 54]. Through both qualitative and quantitative evaluations, we demonstrate that our method consistently produces edits perceived as more creative and aesthetically pleasing compared to baseline methods. By dynamically infusing generative processes with artistic influences, our method expands the boundaries of creative exploration in image editing, offering new avenues for generative artistry. Our contributions are as follows:

- We introduce a novel agentic framework for the task of creative image editing and generation. To the best of our knowledge, this is the first work to introduce the task of ‘creative editing’.
- We incorporate a user-in-the-loop generation setting, enabling user guidance to steer the creative direction through optional interventions. This supports a more collaborative human-AI co-creation process while maintaining artistic coherence and control.
- We demonstrate the versatility of our method across image editing and generation, as well as its potential for enhancing personalization workflows.
- We further highlight the adaptability of our approach by

showcasing its potential applications in creative video generation.

2. Related Work

Text-to-Image Models. Recent advances in diffusion models [26, 57, 59] have revolutionized text-to-image synthesis, enabling high-fidelity image generation guided by textual prompts. Models such as DALLE-3 [50], SDXL [53], and Flux [14] demonstrate the ability to generate visually compelling images based on textual prompts [39, 69, 71]. While these models produce high-quality outputs, they lack a structured mechanism to enforce creativity principles in generation. Personalized generation approaches such as DreamBooth [58] and Textual Inversion [20] focus on fine-tuning text-to-image models for specific subjects or styles. However, these methods optimize for style and subject consistency rather than generating creative images.

Creative Image Generation and Editing. Research on creative generation in AI has advanced through GANs [22, 32] and diffusion models, leveraging contrastive loss and diversity-based objectives to encourage novel synthesis beyond category constraints [13, 25, 60]. Recent works such as ProCreate [40] use energy-based repulsion to steer diffusion models away from reference images, while Inspiration Tree [66] employs hierarchical decomposition for conceptual hybridization. ConceptLab [55] tackles creative concept synthesis through diffusion priors, iteratively enforcing constraints to generate novel category members. Despite their advancements, these methods require expensive retraining or optimization, and fail to generalize to broader concepts. For image editing, ControlNet [77] extends Stable Diffusion, introducing external conditioning signals for localized modifications while maintaining structural integrity. SDEdit [46] and Blended Latent Diffusion [2] refine diffusion-based editing for finer control, while InstructPix2Pix [7] allows text-based transformations via user prompts. However, these approaches focus on structural fidelity rather than creativity-driven, minimal-guidance transformations.

Large Language Models Large Language Models (LLMs) such as GPT-4 [51] and PaLM [9] have demonstrated remarkable capabilities in natural language understanding and generative tasks. These models leverage transformer architectures [64], which allows them to process large amounts of text and generate coherent and contextually relevant outputs. In creative domains, LLMs have been increasingly integrated into AI-driven artistic workflows, assisting with idea generation, structured prompt synthesis, and artistic guidance [45]. GenArtist [68] uses a multimodal single agent for general image generation and editing but does not address creative image editing and fails to leverage the collaborative nature of multiple agents for complex use cases. Several studies have explored LLMs in the context of cre-

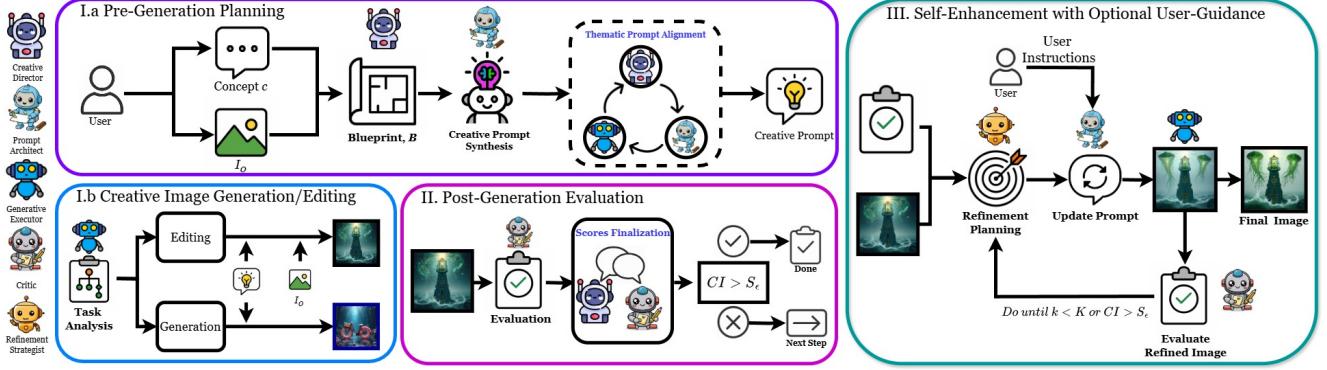


Figure 2. **CREA Framework.** We introduce a collaborative multi-agent framework for creative image editing and generation. Our framework consists of four stages, 1.a Pre-Generation Planning, 1.b Creative Image Generation/Editing, 2. Post-Generation Evaluation and 3. Self-Enhancement. Here, K is the number of maximum iterations.

activity [10, 18, 34, 35, 41, 80]; however, to the best of our knowledge, creative editing tasks have not been explicitly tackled before. Additionally, agentic frameworks—where AI systems exhibit autonomy in decision-making, iterative refinement, and adaptive goal-setting—have not yet been systematically explored in the context of creative image generation or editing.

3. Methodology

Creativity is a multifaceted process that involves ideation, refinement, evaluation, and the ability to balance novelty with coherence. Traditional generative AI systems, however, often rely on static, single-step processes, where outputs are determined by a fixed prompt-to-output pipeline, limiting adaptability and fine-grained control. In contrast, an agentic framework provides a more dynamic and interactive approach by coordinating multiple AI agents that can reason, collaborate, and iteratively refine creative outputs. By structuring creativity as a multi-agent process, our system mirrors human collaborative workflows, where distinct roles—such as conceptualization, critique, and enhancement—work in tandem to push creative boundaries while ensuring coherence and quality. We describe the key components of our framework below. Also, please see Fig. 2 and Algorithm 1 for an overview of our framework.

3.1. Multi-Agent Framework Design

Our workflow mirrors structured human collaboration, assigning distinct agent roles to ensure iterative, controllable creative image editing and generation where agents are:

Creative Director A_1 . This agent serves as the main decision-maker, interpreting concepts, defining a creativity blueprint, and coordinating with agents to refine, discard, or finalize the image.

Prompt Architect A_2 . Translates conceptual ideas

into contrastive prompts [8] for each creativity principle, merging them into a high-creativity prompt for the *Generative Executor* agent for image editing/generation and refining them iteratively based on agent feedback.

Generative Executor A_3 . This agent uses T2I models such as Flux [14] and ControlNet [77] for image generation or editing, dynamically selecting the appropriate diffusion model and parameters to ensure creative outputs.

Art Critic A_4 . The Art Critic evaluates the generated image based on the creativity principles, assigning a score for each criterion. Given that LLMs can approximate human judgment in subjective evaluations [81], this agent uses a multimodal LLM judge to ensure sensible evaluation.

Refinement Strategist A_5 . This agent translates the Critic’s feedback into actionable refinements for the next iteration. It identifies weak creative dimensions and suggests precise modifications to the *Prompt Architect*.

Each agent maintains a private memory and utilizes role-specific tools to share task status and relevant information, ensuring informed decision-making at every step. See Section C.4 in the Supplementary Material for detailed agent compositions.

3.2. Collaborative Agentic Synthesis

Given a user-provided concept c (such as ‘a guitar’ and an input image I , our goal is to modify it to generate I_c in a creative and disentangled manner. For image generation, we follow the same pipeline with minimal modifications to produce a creative image I_0 and transform it into I_c . We formulate this as an optimization problem that maximizes a Creativity Index (CI), guided by six creativity principles described below. Our method has three modular phases: *Pre-Generation Planning*, *Post-Generation Evaluation*, and *Self-Enhancement with optional User-Guidance*. For clar-

Algorithm 1 CREA Method Overview

Input: User concept c or Initial image I_0 , Max iterations K , Creativity threshold S_ϵ
Given: Creativity principles template, T
Init: Agents $\{\mathcal{A}_1 : \mathcal{A}_5\}$

Pre-Generation Planning

- 1: **if** generation task **then**
- 2: $\mathcal{A}_1 \rightarrow B$ from c
- 3: **else if** editing task **then**
- 4: $\mathcal{A}_1 \rightarrow B$ from I_0 (initial generation/user-provided)
- 5: **end if**
- 6: $\mathcal{A}_2 \rightarrow P = \{p_1, p_2, \dots, p_6\}$
- 7: $\mathcal{A}_2 \rightarrow P_c = \text{CoT-Fusion}(P)$
- 8: $\mathcal{A}_3 \rightarrow \text{Validate } P_c$, adjust model parameters

Image Synthesis and Editing

- 9: **if** Generating a new image **then**
- 10: $I_0 = G(P_c, \theta)$
- 11: **else if** Editing an existing image **then**
- 12: $I_e = G(P_c, I_0, \theta)$
- 13: **end if**

Post-Generation Evaluation

- 14: $\mathcal{A}_4 \rightarrow S = \{S_1, \dots, S_6\}$ for I_e
- 15: Compute $CI = \sum_{i=1}^6 S_i$, $S_i \in [1, 5]$
- 16: **if** $CI \geq S_\epsilon$ **then**
- 17: **return** I_e as I_c
- 18: **else**
- 19: Proceed to refinement phase
- 20: **end if**

Self-Enhancement with Optional User-Guidance

- 21: **for** $k = 1$ to K **do**
- 22: $\mathcal{A}_5 \rightarrow$ Identify weak S_i , suggest refinements
- 23: $\mathcal{A}_2 \rightarrow P_r = P_e + \Delta P$ \triangleright refined prompt, P_r
- 24: $\mathcal{A}_3 \rightarrow I_r = G(P_r, I_k, \theta)$ \triangleright intermediate image, I_r
- 25: $\mathcal{A}_4 \rightarrow S = \{S_1, \dots, S_6\}$ for I_r \triangleright refined image, I_r
- 26: **if** $CI \geq S_\epsilon$ **then**
- 27: **return** I_r as I_c
- 28: **end if**
- 29: **end for**

Output: Final high-creativity image I_c

ity, the following sections primarily describe our method in the context of creative editing, as the same framework extends naturally to image generation with minor adjustments.

Creativity Principles. Our framework leverages six creativity principles, grounded in state-of-the-art creativity theories, to systematically evaluate and measure creative output. *Originality*, measuring novelty and uniqueness, is inspired by Boden’s Theory of Creativity [5] and Guilford’s Divergent Thinking [23] framework. *Expressiveness*, which captures emotional impact, is influenced by

Amabile’s Model of Creativity [1] and Ramachandran & Hirstein’s Laws of Aesthetics [54]. *Aesthetic Appeal*, assessing composition and harmony, is grounded in Martindale’s Aesthetic Model [44] and Berlyne’s Aesthetic Theory [3]. *Technical Execution*, evaluating craftsmanship and skill, draws from Amabile’s Model and AI Creativity Frameworks [1]. *Unexpected Associations*, reflecting surprise and ingenuity, is supported by the Geneplore Model [17] and Boden’s Combinational Creativity [5]. Finally, *Interpretability & Depth*, which considers exploration potential, is informed by Ramachandran’s Laws [54] and the Geneplore Model [17] (see Appendix for more details). These six principles are used as a creativity template T for agents to assess and refine the outputs.

3.2.1. Pre-Generation Planning and Image Synthesis

The pre-generation planning phase serves as a structured ideation stage where agents collaboratively establish a creative blueprint, B before image generation begins. This phase involves three key agents: the Creative Director A_1 , Prompt Architect A_2 , and Generative Executor A_3 , who collaboratively devise the creativity prompt P_c that is both creatively rich and technically viable. First, *Creative Director*, A_1 interprets the initial image I_0 , either user-provided or generated using the user-provided concept c to formulate a creativity blueprint B , capturing the core theme, stylistic interpretation, visual structure, and necessary constraints to balance artistic flexibility with semantic coherence (see Appendix for more details). Based on B , the *Prompt Architect* A_2 synthesizes a set of contrastive prompts $P = \{p_1, p_2, \dots, p_6\}$, each conditioned on a distinct creativity principle and are merged into a high-creativity fused prompt P_c through Chain-of-Thought [70] reasoning:

$$P_c = \text{CoT-Fusion}(p_1, p_2, \dots, p_6) \quad (1)$$

where CoT-Fusion extracts salient conceptual and stylistic attributes from each prompt and synthesizes them into a coherent, balanced, and conceptually rich formulation. The *Generative Executor* A_3 evaluates the feasibility of P_c and determines T2I model-specific constraints-such as ControlNet conditioning scale, image guidance scale to anticipate the nuances of the generated blueprint. Once all agents reach a consensus, the prompt moves to the next phase for creative image generation.

Image Generation: The *Generative Executor*, A_3 plays a dual role, either generating a creative image using a T2I model or performing disentangled creative editing on an existing image, whether initially generated (I_0) or user-provided (I_0). The high-creativity structured prompt formulated during the pre-generation planning phase is then taken by the *Generative Executor* to synthesize the initial creative image, I_0 using a text-to-image diffusion model, G as:

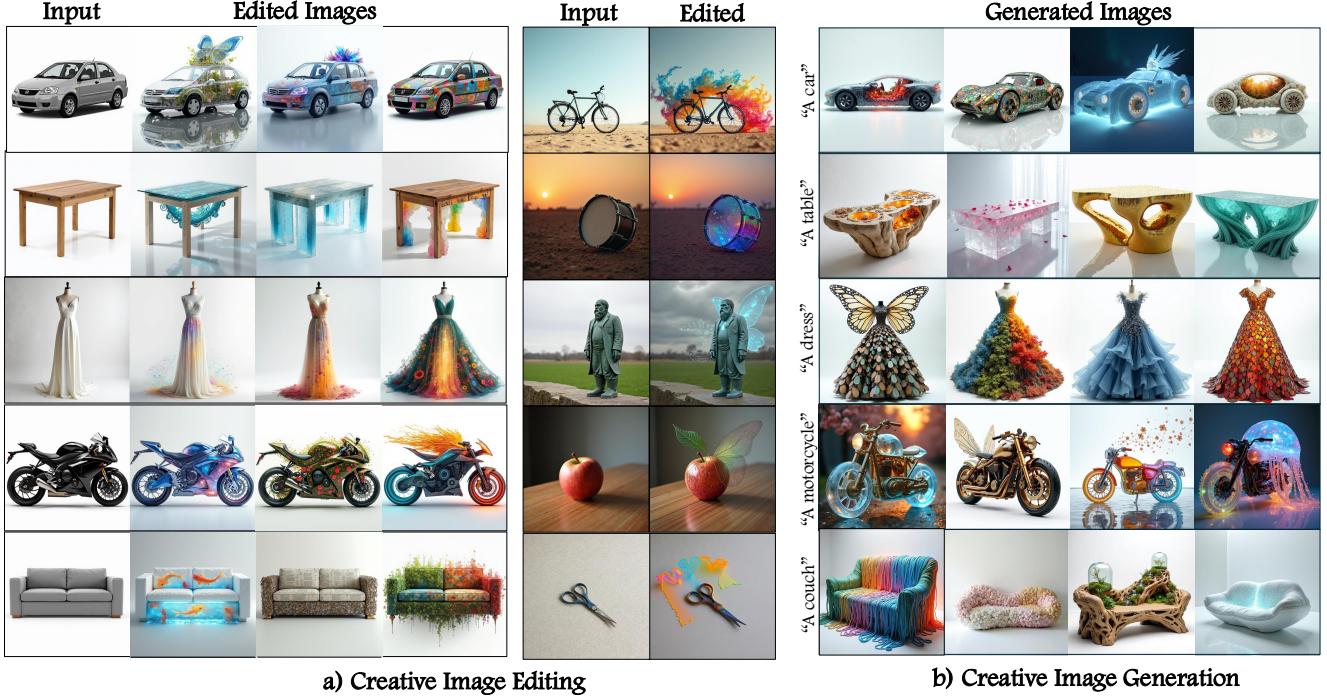


Figure 3. **Qualitative Results for Creative Image Editing and Generation Tasks.** (a) Qualitative results illustrating CREA’s disentangled creative edits. (b) Generation results across diverse objects and domains, demonstrating CREA’s ability to produce a wide range of creative variations. For more results, please visit Supplementary Material.

$$I_0 = G(P_c, \theta) \quad (2)$$

where θ represents model-specific parameters—such as guidance scale and ControlNet conditioning scale. The generated image, I_0 serves as the starting point for the creative editing and iterative refinement process as described in the following sections.

Image Editing: If the user provides an image instead of generating one, or if an enhancement to I_0 is required, the *Generative Executor* performs disentangled creative edits using

$$I_e = G(P_c, I_0, \theta) \quad (3)$$

where G is the ControlNet model used to perform disentangled edits, P_c is the high-creativity editing prompt generated in the pre-generation planning phase and θ represents parameters of G . After generation or editing, the resulting image progresses to the post-generation evaluation phase to investigate if further iterative refinements are necessary.

3.2.2. Post-Generation Evaluation

The post-generation evaluation phase assesses the edited creative image, I_e (or I_0 for generation) against the creativity template, T to maximize creativity. This Critic A_3 and

the Creative Director A_1 collaborate, with the *Critic* systematically evaluating the initial edited image, I_e based on the creativity template, T . The *Critic* utilizes the LLM-as-a-Judge framework [81] to evaluate the edited image I_e by assigning a creativity score, S_i for each of the six i^{th} creativity criteria on a 1-5 scale. The overall Creativity Index, CI is then computed as:

$$CI = \sum_{i=1}^6 S_i, \quad S_i \in [1, 5] \quad (4)$$

If the total creativity score, $CI < S_\epsilon$, where S_ϵ is a pre-defined threshold, the edited image I_e is considered sub-optimal in creativity. The *Creative Director* then reviews the *Critic*’s evaluation and may challenge its assessment if the assigned scores misalign with the creative blueprint, B . Once a consensus is reached, I_e is either finalized or progresses to the next phase for further enhancement based on the final creativity score CI .

3.2.3. Self-Enhancement with Optional User-Guidance

While one round of editing produces optimal creative outputs, further refinement can enhance creativity. In the self-enhancement phase, all agents iteratively refine the edited image, I_e with optional human intervention. Given a maximum of K iterations, each edited image I_k is evaluated by

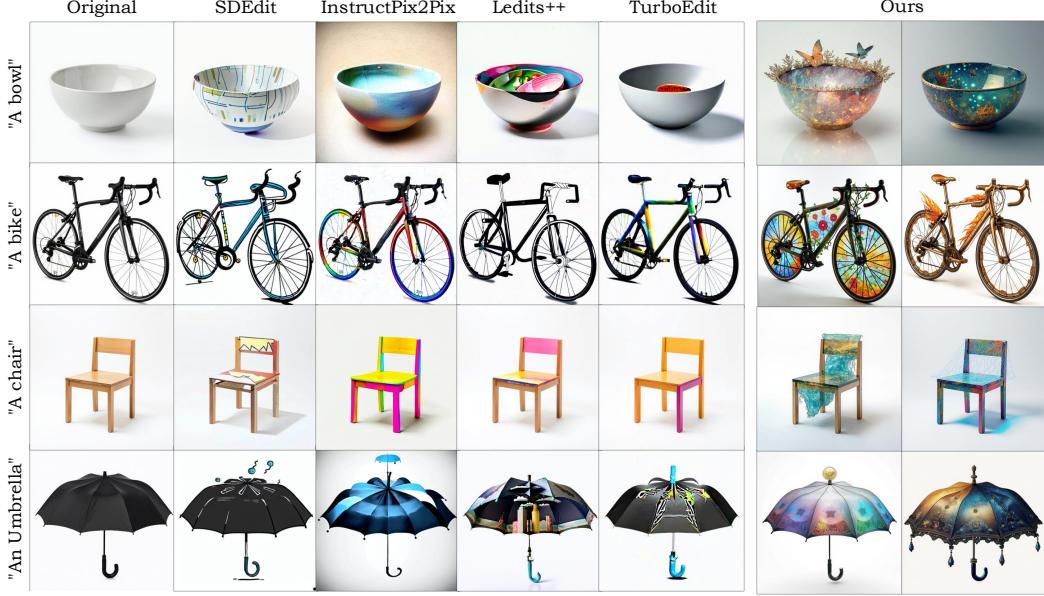


Figure 4. **Qualitative Comparison of Creative Image Editing Task.** We compare CREA with state-of-the-art editing methods. As shown, CREA successfully reimagines objects into creative variants in a disentangled manner, whereas other approaches either fail to produce distinctly creative edits or introduce unintended alterations.

the *Critic* to compute its CI . When $CI < S_\epsilon$, the *Refinement Strategist*, A_5 identifies the low scoring creative dimensions and proposes a refinement plan to enhance the corresponding weak dimensions, which the *Prompt Architect* A_2 uses to refine the editing prompt, P_e as follows:

$$P_r = P_e + \Delta P \quad (5)$$

where ΔP represents the prompt adjustment that amplify specific creativity dimensions based on their evaluation scores and P_r is the refined creativity prompt. The refined prompt is used by the *Generative Executor* A_3 to regenerate an improved image using:

$$I_r = G(P_r, I_k) \quad (6)$$

The process iterates until $CI \geq S_\epsilon$ or $k \geq K$, where K is the maximum allowed iterations and I_k is an intermediate creative image. Users can provide real-time instructions to enhance creativity, which the *Prompt Architect* integrates into the evolving prompt, while the *Refinement Strategist* ensures artistic coherence. The final goal is:

$$\max_{I_c} \mathbb{E}[CI(I_c)] \quad (7)$$

where I_c is the final optimized image, achieved through iterative refinement of the refined current image, I_r .

4. Experiments

Experimental Setup In this section, we evaluate our method’s ability to generate highly creative edits and images. All experiments use FLUX.1-dev¹. For editing, we employ ControlNet² with a conditioning scale of 0.4. For image generation, we vary the CFG scale from 3.5 to 40 to explore different levels of creativity and control. Additionally, we utilize Autogen [72] for our agentic framework. All experiments are performed on an NVIDIA L40 GPU. We use GPT-4o as our MLLM for all agents [51]. We use QWEN2.5-VL-32B for MLLM as a judge metrics [15]. We set the Creativity Index (CI) to 24 for editing tasks and 26 for generation tasks with maximum number of iterations as $K = 3$. A full run of the pipeline takes approximately 3–5 minutes, depending on the number of self-enhancement rounds. Our source code will be publicly available.

4.1. Qualitative Results

Creative Image Editing First, we qualitatively showcase how CREA transforms input images into various creative modifications. As seen in Fig. 3, CREA’s autonomous agents analyze the input image or concept and generate creative prompts—e.g., focusing on style, color, or thematic twists—without requiring extensive user intervention. Since no existing method is explicitly designed for creative image editing, we adapt state-of-the-art editing models for

¹<https://huggingface.co/black-forest-labs/FLUX.1-dev>

²<https://huggingface.co/InstantX/FLUX.1-dev-Controlnet-Union>

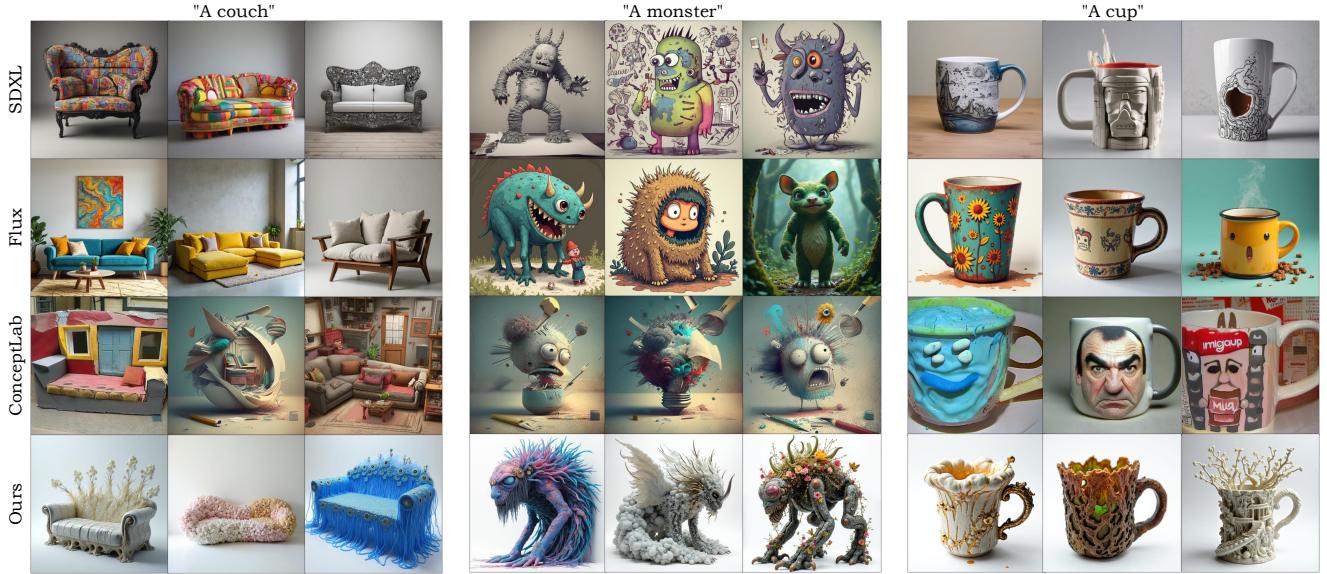


Figure 5. **Qualitative Comparison of Creative Image Generation Task.** We compare CREA with ConceptLab, SDXL and Flux. CREA consistently produces diverse and creative generations across multiple domains.

Method	CLIP \uparrow	LPIPS* \uparrow	VENDI \uparrow	DINO \uparrow	User Study-Q1	User Study-Q2
LEDITS++	0.396 ± 0.028	0.252 ± 0.074	2.88 ± 1.11	0.678 ± 0.160	3.21 ± 1.27	3.50 ± 1.25
InstructPix2Pix	0.379 ± 0.032	0.289 ± 0.126	1.94 ± 0.61	0.704 ± 0.189	3.14 ± 1.23	3.59 ± 1.17
SDEdit	0.381 ± 0.033	0.308 ± 0.068	3.19 ± 1.23	0.737 ± 0.162	3.31 ± 1.21	3.15 ± 1.16
TurboEdit	0.389 ± 0.031	0.192 ± 0.071	2.34 ± 0.94	0.735 ± 0.173	3.23 ± 1.29	2.63 ± 1.20
Ours (Editing)	0.417 ± 0.030	0.414 ± 0.157	3.70 ± 1.97	0.744 ± 0.185	3.34 ± 1.34	3.74 ± 1.21
SDXL	0.404 ± 0.033	0.636 ± 0.069	6.63 ± 2.85	N/A	4.37 ± 0.99	3.56 ± 1.10
Flux	0.359 ± 0.048	0.650 ± 0.088	5.84 ± 2.69	N/A	4.11 ± 1.27	3.00 ± 1.24
ConceptLab	0.334 ± 0.055	0.663 ± 0.076	10.38 ± 2.27	N/A	3.40 ± 1.52	3.18 ± 1.30
Ours (Generation)	0.360 ± 0.052	0.709 ± 0.057	10.44 ± 2.15	N/A	4.32 ± 0.99	4.16 ± 1.01

Table 1. **Quantitative Comparison of Creative Image Editing and Generation.** Our method surpasses state-of-the-art methods across multiple metrics for both editing and generation tasks. Note that DINO scores cannot be computed for image generation, as they rely on image-image similarity, and there is no reference image available for this task. * indicates that scores are interpreted in opposition to their conventional usage as creative generation task benefits from greater perceptual distance between the original and edited images.

comparison. Specifically, we evaluate the following baselines: LEDITS++ [6], InstructPix2Pix [7], SDEdit [46] and TurboEdit [11]. For a fair comparison, we apply a “creative <object>” prompt (e.g., “a creative couch”) to the baseline methods, mirroring the objective of CREA. As shown in Fig. 4, standard editing methods often fail to generate distinctly creative concepts: InstructPix2Pix typically adds vibrant colors or alters the background extensively without fundamentally reimagining the object. LEDITS++, SDEdit, and TurboEdit struggle to introduce creative features beyond superficial stylistic changes. In contrast, CREA successfully performs creative edits in a disentangled manner.

Creative Image Generation For creative image generation,

we compare CREA against ConceptLab [55], which is the closest related approach, as well as two generative baselines: Flux [14] and SDXL [53]. To ensure a fair comparison, we use the same random seed for each method in every evaluated prompt, allowing for direct visual comparisons. As illustrated in Fig. 5, CREA consistently produces diverse and creative generations across multiple domains. In contrast, ConceptLab struggles to maintain the intended concept, particularly for highly abstract or unconventional categories. For example, when generating “a monster,” ConceptLab often fails to produce a meaningful interpretation, as it relies on extracting subcategories from the BLIP model. If a given concept lacks well-defined subcategories

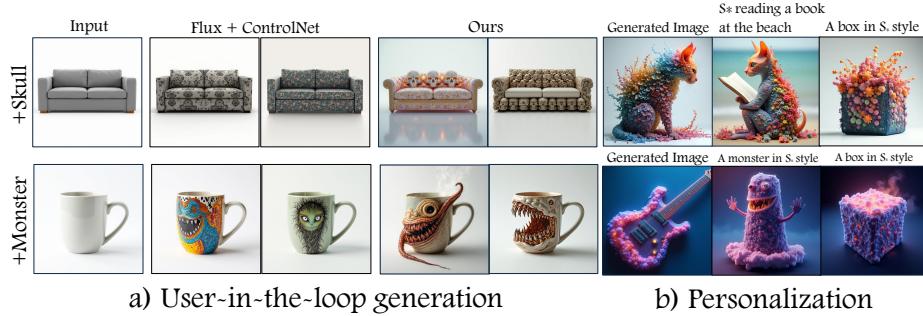


Figure 6. **Creative applications of our method beyond image generation and editing.** (a) Users can steer the creative process with additional conditions such as ‘Monster’. (b) CREA-generated images can be leveraged for personalization in creative domains.

or consists of highly specific attributes, ConceptLab’s fails to perform well. CREA, on the other hand, generalizes across a broad range of creative categories without relying on predefined subcategory constraints.

4.2. Quantitative Results

For both editing and generation, we utilized 24 different objects with 25 prompts (either for editing or generation), resulting in an evaluation set of 600 images per task.

Creative Image Editing. For image editing, we compare our method against state-of-the-art techniques, including LEDITS++, InstructPix2Pix, SDEdit, and TurboEdit, across a range of evaluation metrics. To assess how well the edited objects align with the text descriptions, we compute the CLIP score by measuring the similarity between the generated image and its corresponding text prompt. For evaluating diversity, we use the LPIPS [78] score, which quantifies perceptual distance between images. Unlike conventional usage where lower LPIPS indicates better reconstruction, a higher LPIPS in our case signifies stronger, more transformative edits—a desirable trait in creative tasks. Additionally, we compute the DINO [76] score which measures how well the edited image retains key structural and semantic characteristics of the original image, and Vendi [19] score, which quantifies diversity by calculating the Shannon entropy of the eigenvalues of the similarity matrix among the generated images. As shown in Table 1, our method consistently outperforms all baselines across all evaluation metrics, demonstrating its superior ability to generate creative and diverse image edits.

Creative Image Generation. For creative image generation, we compare CREA against ConceptLab, Flux, and SDXL. As shown in Table 1, our method achieves superior results in LPIPS and VENDI scores, while in CLIP scores, it was outperformed by SDXL. We observe that SDXL tends to generate highly colorful images, which aligns with CLIP’s depiction of creativity. However, it produces the lowest LPIPS scores, indicating that its generated images are highly similar to each other, and it also achieves signif-

icantly lower VENDI scores compared to CREA and ConceptLab. While ConceptLab and our method achieve comparable results overall, ConceptLab has significantly lower performance CLIP scores, suggesting that its generated images do not align well with the text prompt. This limitation stems from ConceptLab’s reliance on well-defined subcategories—a core design principle of their method. As shown in Fig. 5, ConceptLab fails when a concept lacks sufficient subcategories, such as its inability to accurately generate a couch object. While ConceptLab attains a high VENDI score, this failure highlights its trade-off between diversity and semantic alignment, limiting its effectiveness.

LLM as a Judge. We use a Multi-modal LLM [15] as a judge to provide a scalable and consistent evaluation of creative image edits, as traditional quantitative metrics (e.g., LPIPS or CLIP) fail to capture subjective qualities like originality, expressiveness, and aesthetic appeal. Therefore, we used LLM as a judge and compared methods for several key aspects of creativity, including Originality, Expressiveness, Aesthetic Appeal, Technical Execution, Unexpected Associations, Interpretability and Depth, and Overall Creativity, simulating human-like subjective assessments [12]. As shown in Table 2, our results significantly outperform other methods across all evaluated aspects, demonstrating the effectiveness of our approach in generating more diverse, meaningful, and visually compelling creative edits.

User Study. To assess the creativity of the generated images based on human perception, we conducted a user study where participants evaluated images using three key criteria. Usability measures how accurately the generated image represents the specified object (Q1). Novelty assesses the uniqueness and originality of the image (Q2). For edited images, we evaluate editing consistency, which examines how well the characteristics of the original image are preserved while incorporating creative modifications (Q1). We run our user study on Prolific.com with 50 participants. Participants rated each criterion on a 5-point Likert scale, ranging from 1 (Not at all) to 5 (Very well). The study was conducted across a diverse set of generated and edited images,

Method	Originality ↑	Expressiveness ↑	Aesthetic ↑	Technical ↑	Unexpected ↑	Interpretability ↑	Total ↑	Creativity ↑
LEDITS++	3.04 ± 0.74	2.52 ± 0.66	3.56 ± 0.55	3.80 ± 0.47	2.86 ± 0.84	2.60 ± 0.71	18.38 ± 3.37	77.80 ± 8.83
InstructPix2Pix	2.43 ± 0.91	2.28 ± 0.80	3.59 ± 0.54	3.76 ± 0.51	2.12 ± 0.82	2.21 ± 0.78	16.39 ± 3.70	69.78 ± 15.94
SDEdit	2.50 ± 0.87	2.12 ± 0.72	3.35 ± 0.50	3.59 ± 0.51	2.12 ± 0.78	2.07 ± 0.72	15.74 ± 3.42	69.39 ± 13.54
TurboEdit	2.68 ± 0.76	2.12 ± 0.62	3.28 ± 0.50	3.66 ± 0.47	2.44 ± 0.78	2.12 ± 0.62	16.30 ± 3.11	71.34 ± 13.87
Ours (Editing)	3.77 ± 1.00	3.49 ± 1.03	4.49 ± 0.62	4.61 ± 0.55	3.66 ± 1.12	3.46 ± 1.03	23.48 ± 4.95	83.47 ± 6.68
SDXL	3.45 ± 0.89	3.30 ± 0.77	4.15 ± 0.52	4.31 ± 0.49	3.33 ± 1.00	3.32 ± 0.79	21.85 ± 3.91	82.95 ± 6.56
Flux	2.87 ± 0.69	3.05 ± 0.74	4.12 ± 0.54	4.17 ± 0.47	2.59 ± 0.78	2.86 ± 0.64	19.66 ± 3.14	79.46 ± 7.82
ConceptLab	3.49 ± 0.75	3.32 ± 0.84	3.75 ± 0.77	3.93 ± 0.71	3.42 ± 0.83	3.34 ± 0.81	21.25 ± 4.13	80.99 ± 6.84
Ours (Generation)	4.39 ± 0.69	4.55 ± 0.54	4.98 ± 0.16	4.96 ± 0.20	4.39 ± 0.70	4.42 ± 0.64	27.68 ± 2.55	89.87 ± 4.04

Table 2. **Quantitative Comparison of Creative Image Editing and Generation using LLM-as-a-judge.** We used a multi-modal LLM as a judge [15] for simulating human-like subjective assessments across several key aspects of creativity. Our method surpasses state-of-the-art methods across all aspects for both editing and generation tasks.

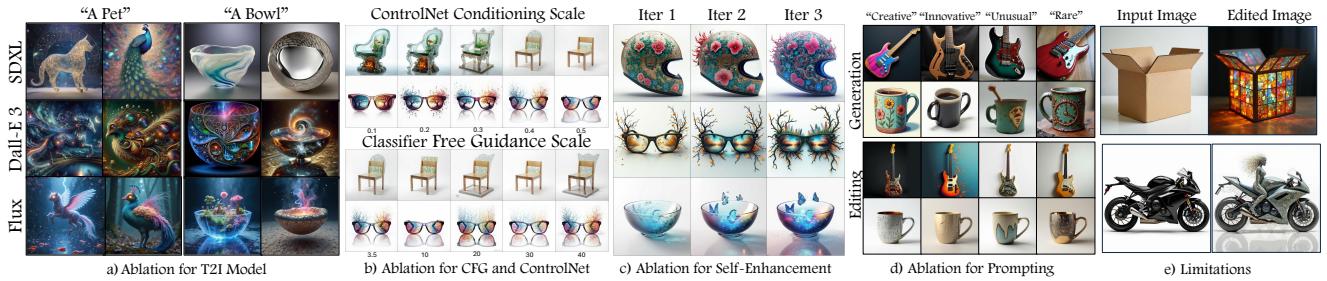


Figure 7. **Ablation Study.** We perform comprehensive ablation studies to analyze the design choices of CREA: (a) Model Generalization: Our method extends effectively to different generative models, such as SDXL and DALL-E. (b) Parameter Sensitivity: We ablate CFG values for Flux and the conditioning scale for ControlNet to evaluate their impact. (c) Iterative Refinement: We demonstrate the benefits of our method’s refinement process over multiple iterations. (d) Prompt Variations: We explore alternative prompts beyond ‘a creative <obj>’. For additional ablation results, please refer to Table 3.

providing a comparative analysis of our method against existing baselines.

4.3. Additional Experiments

User-Guided Editing and Generation Our method enables users to guide the creative process according to their preferences (see Fig. 6 (a)). For example, users can specify not only that a creative edit should be applied to a cup but also include additional conditions, such as ‘monster’, to influence the generation. Our approach incorporates these preferences, steering the creative process accordingly. Compared to the baseline Flux + ControlNet approach, where we provided the prompt ‘A creative <condition> <object>’, our results demonstrate greater creativity while still complying to the given conditions.

Personalization To highlight the broader applicability of our approach, we present personalization results using CREA-generated creative images using an off-the-shelf personalization adapter [67]. Fig. 6 (b) demonstrates how generated subjects can be adapted to various contexts or how their styles can be transferred to create new images. Note that due to the limitations in personalization models, some fine-grained details were not able to capture by [67], how-

ever the main characteristics are still preserved.

Video Generation To demonstrate the versatility and extensibility of our agentic framework, we extend CREA to creative video generation, where an initial prompt (e.g., ‘a train’) is automatically transformed into creative scenes. We conduct experiments using the CogVideoX [74] model as the generative backbone. Instead of initializing the process with a static creative blueprint, our Creative Director agent generates a structured creative *video plan* containing key fields: *Subject*, *Action*, *Setting*, *Style*, and optional *Additional Details*. This plan is passed to the Prompt Architect, who composes a coherent and high-creativity video prompt via contrastive prompt fusion, similar to our image generation pipeline. The Generative Executor then synthesizes the video using CogVideoX. This evaluation serves as a proof of concept for applying our multi-agent creativity principles beyond static imagery. As shown in Figure 8, our method produces significantly more imaginative and visually engaging results compared to baseline prompts such as “a creative <object>.”

Ablation Studies We perform comprehensive ablation studies to analyze the design choices of CREA (see Fig. 7). (a) **Ablation on Generalization to other T2I models:** Our

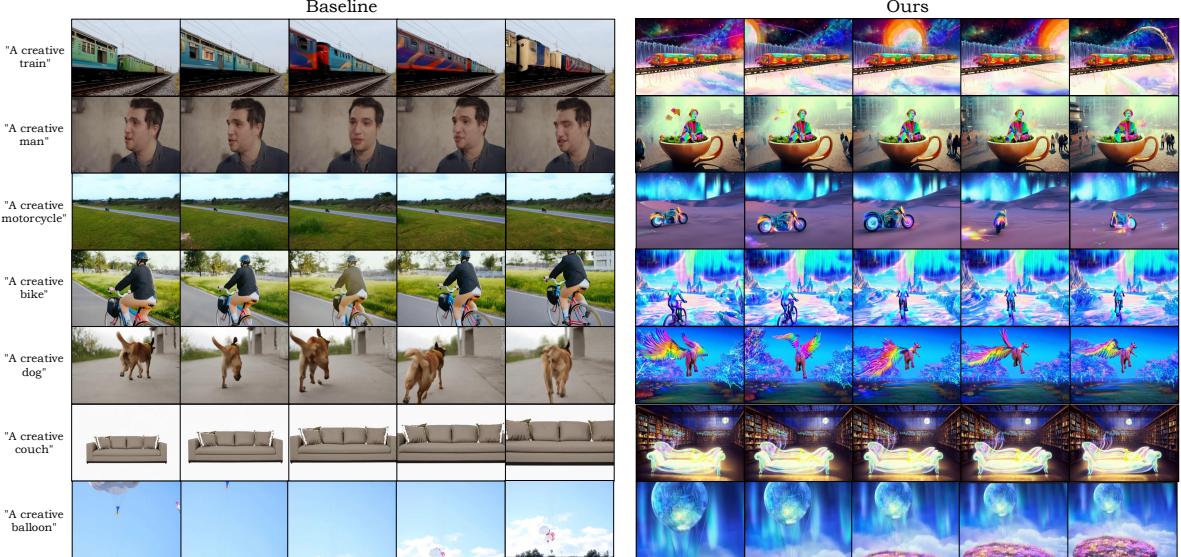


Figure 8. **Video Generation.** Comparison between baseline generations from CogVideoX and outputs generated using our creative agentic pipeline. Our method enables the creation of visually diverse and creative video scenes.

Method	LPIPS-Diversity \uparrow	Vendi \uparrow	Creativity (LLM) \uparrow
Base	0.302 ± 0.129	3.19 ± 1.49	79.67 ± 9.66
+Principles	0.312 ± 0.142	3.59 ± 2.46	81.41 ± 7.76
+Contrastive	0.391 ± 0.150	3.50 ± 1.64	82.31 ± 6.98
+Self-Enhancement	0.414 ± 0.157	3.70 ± 1.97	83.47 ± 6.68

Table 3. **Ablation Study for CREA.** CREA achieves the highest performance across all metrics when all components are utilized, demonstrating the effectiveness of our full framework.

method extends effectively to different generative models, such as SDXL and DALL-E. (b) **Ablation on Parameter Sensitivity:** We ablate CFG values (3.5-40) for Flux and the conditioning scale for ControlNet (0.1-0.5) to evaluate their impact. (c) **Ablation on Iterative Refinement:** We demonstrate the benefits of our method’s refinement process over multiple iterations. (d) **Ablation on Prompt Variations:** We explore alternative prompts beyond ‘a creative <obj>’ and test negative prompting (e.g., ‘a normal <obj>’, see Fig. 11) to steer the model away from conventional generations. (e) **Ablation on Model Components** We conduct an ablation study on key components of our framework, including creativity principles, contrastive prompting, and refinement (see Table 3). The base version represents a baseline where the multi-modal LLM model is simply prompted to generate a creative description for a given object.

5. Limitations

While our framework introduces a novel agentic approach to creative image editing and generation, we would like to address a few limitations. Since our framework utilizes a T2I model such as Flux, certain biases inherent to the

generative backbone can affect the outputs. For instance, we observe cases where the background is unintentionally darkened based on the object’s semantics (e.g., editing a “lighted box” often results in darker surroundings to emphasize contrast), or where the model hallucinates human figures even when not prompted (see Fig. 7 (e)). In addition, while CREA extends naturally to video generation using models such as CogVideoX, this extension introduces new challenges since attributes like abstraction or surrealism may unintentionally amplify inconsistencies in motion. Nonetheless, our framework represents a significant step toward enabling autonomous and collaborative creativity in AI. By modeling a multi-agent dialogue grounded in creativity principles, CREA pushes beyond traditional prompt-based pipelines to achieve more creative outputs.

6. Conclusion

In this work, we introduce a novel agentic framework for creative image editing and generation, pioneering a disentangled approach that enables greater flexibility and artistic control. By leveraging specialized agents that collaborate to refine and enhance outputs, our method overcomes the limitations of traditional prompt-to-image models, reducing the burden on users while fostering creativity. We demonstrate the versatility of our approach across editing and generation, and highlight its potential for creative video generation. Our findings suggest that agentic frameworks can serve as a powerful foundation for more autonomous and creative AI systems, opening new directions for creative collaboration between humans and AI.

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CREA: A Collaborative Multi-Agent Framework for Creative Content Generation with Diffusion Models

Supplementary Material

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A. Investigating Creativity Types

Investigating Creativity Types We investigate emerging patterns in generated images to identify key attributes—shape, color, and texture—that influence creativity. Our analysis reveals that our method achieves significantly higher scores in these aspects, leading to the generation of more visually diverse and imaginative objects (see Fig. 9). Compared to baseline models, our approach demonstrates a stronger ability to manipulate these factors, reinforcing its effectiveness in producing unique and aesthetically rich generations.

We also investigate emerging factors for different objects within our method (see Fig. 10).

B. Creativity Principles in the Context of AI

B.1. Theoretical Foundations of Creativity

The study of creativity in artificial intelligence (AI) traverses an extensive scholarly terrain, drawing on insights from cognitive psychology, aesthetics, neurobiology, computer science, and beyond. Table 4 in this work identifies several key criteria - Originality, Expressiveness, Aesthetic Appeal, Technical Execution, Unexpected Associations, and Interpretability and Depth that underpin our creativity assessment framework. These criteria are not arbitrary; rather, they reflect foundational theories such as Boden’s categorization of creativity [5], Guilford’s notion of divergent thinking [23], Amabile’s model of social and motivational factors [1], and neuroaesthetic concepts rooted in the works of Ramachandran and Hirstein [54]. These theories collectively provide a robust foundation for understanding creativity as both a human and machine-driven phenomenon. But how does AI actually manifest these traits?

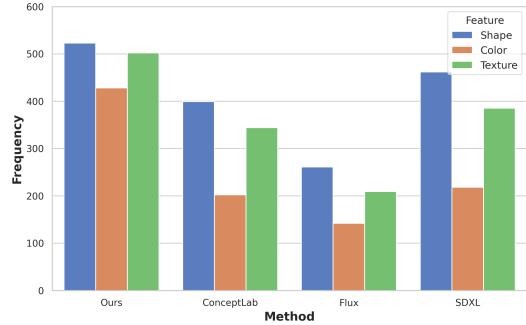


Figure 9. Emerging patterns in the generated images across CREA, ConceptLab, Flux, and SDXL reveal that our method achieves significantly higher scores in shape, color, and texture, enabling the generation of more creative objects.

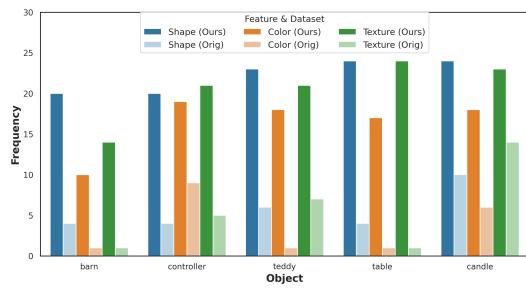


Figure 10. Emerging patterns in the generated images across various objects reveal that our method dynamically emphasizes different factors—such as shape, color, or texture—depending on the object, effectively enhancing creativity in a context-aware manner.

B.2. Computational Creativity: Capabilities, Gaps

By aligning computational methods with these established principles, researchers can better navigate the complexities of what it means for an AI system to be ‘creative’.

Human-centric views on creativity have traditionally emphasized cognitive mechanisms, motivational influences, and cultural contexts. Boden’s theory, for example, delineates creativity into combinational, exploratory, and transformational processes, each capturing an increasingly profound conceptual shift in how ideas are generated and modified.

In AI, combinational creativity can be observed when generative models—particularly Generative Adversarial Networks (GANs) blend stylistic elements from multiple art traditions into hybrid images [22]. While this merging of features may appear novel, it typically does not fundamentally alter the conceptual space from which the models operate, illustrating the difficulties systems still face in achieving transformational creativity. Guilford’s pioneering work on divergent thinking underscored the importance of producing multiple, varied solutions [23]. AI-driven text-generation platforms like GPT-3 and GPT-4 [51] do mimic aspects of divergent thinking by offering an abundance of plausible completions (Brown et al., 2020). Nevertheless, the question persists as to whether these outputs merely recombine learned statistical patterns or truly reflect a leap in imaginative thought.

Beyond cognition alone, Amabile’s componential model highlights how domain-relevant skills, creative processes, and intrinsic motivation intersect to yield creative outputs [1]. This perspective draws attention to the human–machine interface, stressing that creativity often emerges from iterative co-creation rather than algorithmic autonomy. Meanwhile, theories from neuroaesthetics, such as those posited by Berlyne and Ramachandran and Hirshstein, elucidate how phenomena like complexity, novelty, uncertainty, and perceptual principles (e.g., ‘peak shift’) influence artistic and aesthetic preferences (Berlyne, 1971; Ramachandran and Hirshstein, 1999). Although deep learning algorithms like Style Transfer [21] or StyleGAN [21] may inadvertently exploit some of these principles by amplifying salient features, their reliance on learned patterns rather than explicit aesthetic intent underscores the gap between AI-generated novelty and human interpretive nuance. While these examples show impressive generative power, a critical challenge lies in evaluating whether such outputs are truly creative in the human sense.

B.3. Evaluating AI-Generated Creativity

The Geneplore Model provides a useful lens through which to view many large-scale generative models, outlining how a creative process involves both ‘generation’ (forming preliminary mental representations) and ‘exploration’ (refining or recombining these representations) [16]. Transformer-based architectures, with their attention mechanisms, can be seen as ‘geneplore-like’ when they generate multiple potential sequences and then rank or filter them for coherence

[64]. Yet the final outputs typically optimize likelihood or alignment with training data, rather than undergoing any meta-cognitive reflection akin to a human creator’s iterative, intentional revision.

Assessing creativity in AI also demands a balanced approach to formal and subjective metrics. Researchers have developed quantitative measures such as the Frechet Inception Distance (FID) to capture statistical proximity or ‘realism’ [24]. While FID and analogous measures can be informative, they fail to capture nuances of emotional resonance or interpretive richness that many theories consider crucial to truly creative outputs [56]. This motivates a shift from purely statistical benchmarks to human-aligned, multidimensional assessment tools—especially in systems involving co-creation.

B.4. Human-AI Co-Creation in the Future

Although AI models trained on massive datasets produce highly novel outcomes, the iterative nature of human creativity, often involving extensive editing, critique, and context-sensitive judgment, remains only partially replicated in existing machine learning workflows [1]. Systems such as ChatGPT, for instance, enable multi-turn refinements through user inputs [62]. However, they do not spontaneously self-critique or shift creative direction without explicit prompts.

While deep learning has undoubtedly propelled innovation, it seldom delivers truly transformational creativity, as it primarily samples and recombines patterns from existing data rather than fundamentally restructuring conceptual spaces. One promising direction involves placing humans in the loop, harnessing reinforcement learning from human preferences or enabling interactive co-creation scenarios [62]. In such contexts, the interplay of user feedback and algorithmic adaptability can lead to more nuanced, emotionally resonant outcomes. However, this collaboration raises interpretive questions about authorship and creative agency: if the machine contributes significantly to the ideation process, is the creativity emergent from the human artist, the algorithm, or both [43]? These questions underscore that AI creativity is not merely an engineering issue; it is also an epistemological and philosophical inquiry into the nature of creative process itself.

By anchoring AI-based creativity in well-established theoretical frameworks, as we do through the criteria defined in Table 4, researchers and practitioners can adopt a more holistic lens that extends beyond surface-level novelty to capture deeper semantic, aesthetic, and emotional dimensions. While current generative models illustrate significant strides in producing art that appears creative to casual observers, the absence of context-sensitive reflection, domain-specific constraints, and culturally aware interpretive layers hints at the distance yet to be traveled. The path forward

likely lies in hybridizing data-driven models with sophisticated symbolic reasoning, integrating iterative self-critique mechanisms, and maintaining a tight coupling with human feedback loops. This multifaceted approach not only enriches the generative potential of AI but also compels us to revisit and refine our own definitions of what it means to create. Through such rigorous, theory-informed methodologies, we can push AI toward outputs that not only surprise but also resonate with the complexities and depths of human creativity. In aligning theory with implementation, we not only improve generative tools—but also challenge and evolve our own understanding of creativity.

C. LLM-Based Agents

The next-gen AI is famously touted as the ‘Age of Agents’ by many distinguished researchers and for good reasons. Large Language Model (LLM)-based agents represent a significant advancement in AI-driven task automation and decision-making, leveraging the reasoning, contextual awareness, and generative capabilities of LLMs to function as autonomous entities [73]. Unlike traditional rule-based automation or heuristic-driven AI models, LLM-based agents dynamically interpret user input, plan actions, execute complex workflows, and adapt to evolving scenarios. These agents serve as fundamental building blocks for modern AI applications, acting as cognitive intermediaries that integrate natural language understanding (NLU), tool execution, reasoning, and decision-making into a unified system.

LLM agents are intelligent systems that perceive, reason, and act autonomously by leveraging the capabilities of foundation models like GPT-4. As illustrated above, an LLM agent is composed of three core components: Perception, Brain, and Action. The Perception module gathers multimodal inputs (text, images, APIs, sensor data) from the environment, which are then processed by the Brain—the LLM acting as a reasoning core. This brain performs memory retrieval, knowledge grounding, and decision-making to plan suitable responses. Finally, the Action module executes these decisions via natural language outputs, tool usage, or physical actuators. This perception-reasoning-action loop allows LLM agents to operate in dynamic environments, continuously adapting to new tasks and inputs through generalized reasoning and tool-assisted execution.

C.1. Single Agent Systems

A variety of existing LLM-based agent frameworks follow a single-agent paradigm, in which a solitary large language model is augmented with plugins or external capabilities but does not explicitly coordinate with other agents. For example, AutoGPT [61] autonomously pursues user-defined goals by using tools such as a web browser and memory

buffer. Similarly, ChatGPT+ offers a premium plan featuring a code interpreter or plugin ecosystem, enabling program execution or curated tool usage to complete more involved tasks [49]. LangChain Agents [33] provide a modular framework that allows developers to define custom “agents” for action selection (e.g., ReAct agents for reasoning and acting), but they remain single-agent in practice, focusing on how one LLM instance selects and executes a sequence of operations. Transformers Agent [28] offers a similar single-agent mechanism, embedding a set of curated tools to be invoked via natural language instructions. While these single-agent approaches illustrate how LLMs can be augmented with external resources and more sophisticated reasoning loops, their lack of agent-to-agent collaboration can limit problem-solving potential in scenarios where multiple specialized roles or iterative debate might be beneficial.

C.2. Multi-Agent Frameworks

Building on these single-agent foundations, recent frameworks employ multiple, concurrently active LLM-based agents to tackle tasks that may require diverse expertise or role specialization. BabyAGI [75] implements a simple multi-agent pipeline wherein distinct agents handle task creation, task prioritization, and sub-task completion. Although this approach showcases the potential of agent specialization, it enforces a predefined, static communication pattern among agents. CAMEL [37] extends multi-agent design by letting agents converse in assigned “roles” (e.g., user, system, developer) and use an inception-prompting technique for autonomous coordination. However, CAMEL currently does not support tool usage such as code execution. Moreover, works on multi-agent debate demonstrate how multiple LLMs can contest or discuss a problem to improve the factual correctness, reasoning depth, or creative divergence of solutions [38]. These debate-oriented approaches concentrate on structured dialogues between agents but do not natively incorporate human involvement or external tool usage. Meanwhile, MetaGPT [27] is a specialized application of the multi-agent paradigm directed at software development, demonstrating how distributed GPT “roles” can collaboratively design and refine code bases. Due to the rapid evolution of many open-source repositories, the characterizations offered here reflect the state of these systems at the time of writing; readers interested in a more extensive survey are referred to [36].

C.3. Autogen

AutoGen is an open-source framework developed by Microsoft Research’s AI Frontiers Lab [48], designed to simplify the creation and orchestration of AI agent systems to enable seamless multi-agent collaboration by building modular, programmable agents that interact in structured con-

Criterion	Related Theory
Originality (Novelty & Uniqueness)	Boden’s Theory of Creativity, Guilford’s Divergent Thinking
Expressiveness (Emotional Impact)	Amabile’s Model, Ramachandran & Hirstein’s Laws
Aesthetic Appeal (Composition & Harmony)	Martindale’s Aesthetic Model, Berlyne’s Aesthetic Theory
Technical Execution (Craftsmanship & Skill)	Amabile’s Model, AI Creativity Frameworks
Unexpected Associations (Surprise & Ingenuity)	Geneplore Model, Boden’s Combinational Creativity
Interpretability & Depth (Exploration Potential)	Ramachandran’s Laws, Finke et al.’s Geneplore Model

Table 4. Integration of Theories into a Creativity Rating System

versational workflows. At its core, AutoGen provides a unified interface via the `ConversableAgent` base class, from which various specialized agents inherit—such as the `AssistantAgent` for code generation or task completion, the `UserProxyAgent` for human-in-the-loop interactions, and the `GroupChatManager` for coordinating group discussions. Each agent is configured with a `human_input_mode`, system messages, tool-use permissions, and execution constraints, making it easy to orchestrate task-specific, autonomous, or collaborative behaviors. The collaborative framework allows agents to share context, ask clarifying questions, or refine outputs in multiple rounds, supporting complex applications like code debugging, multimodal reasoning, and creative generation. This design facilitates flexible experimentation and customization in agent-based research and real-world use cases. You can check out more about the framework here ([47]).

C.4. CREA’s Multi-Agent Framework Design

CREA is built on a dynamic multi-agent architecture that emulates the collaborative human creative process by distributing cognitive and generative responsibilities across specialized agents. Each agent in the system plays a distinct role and is instantiated using the AutoGen framework’s `ConversableAgent` class, enabling structured communication, tool access, and memory management.

Creative Director (A_1): Acts as the master orchestrator. Powered by GPT-4o, this agent defines the overall creative blueprint, interprets user goals or concepts, and decides whether a generated image meets the creativity criteria. It has functional tools to collaborate with all other agents and a tool to determine if the creativity index, CI is greater than the defined threshold. It does not execute code but uses a shared memory to track blueprint adherence across rounds.

Prompt Architect (A_2): Converts the blueprint into six contrastive prompts based on creativity principles (e.g., Originality, Aesthetic Appeal), which are fused into a high-creativity composite prompt using Chain-of-Thought reasoning. This agent uses GPT-4o and has access to prompt-

fusion tools and tools to interact with other agents, enabling it to translate abstract directives into actionable instructions. It uses the shared memory to track progress, store base templates, and exchange updates.

Generative Executor (A_3): Interfaces with the image generation or editing backend (e.g., FLUX, ControlNet). It has code execution capabilities and is responsible for producing images using prompt, P_c and associated parameters like classifier-free guidance (CFG) or conditioning scales. It can perform both text-to-image generation and disentangled image editing and has access to predefined tools to adjust the hyperparameters of models. In addition, it has tools to manipulate images based on instructions from the CreativeDirector or the User—such as personalization and creative video editing. Its toolbox is highly customizable to incorporate training-free image editing and personalization tools.

Art Critic (A_4): Uses a multi-modal LLM judge (GPT-4o with vision capabilities) to evaluate the image against six creativity criteria. It returns per-dimension scores (1–5 scale) and an aggregate Creativity Index (CI). This agent is crucial for quality control and can challenge previous creative decisions. Art Critic has access to tools to interact with other agents. However, its shared memory has a $window_size = 1$. This is intentional and ensures independent evaluation of each generated creative image, without being influenced by previous evaluations.

Refinement Strategist (A_5): Translates evaluation feedback into actionable prompt refinements. It identifies weak creative dimensions (e.g., low expressiveness) and proposes targeted edits. It works closely with A_2 to iteratively improve the prompt and coordinates with A_3 to re-render improved results. It uses GPT-4o and has access to interaction tools and the shared memory to track information and updates.

A `UserProxyAgent` models Human-in-the-loop and is turned on for optional user-guidance.

C.5. Runtime and Practical Considerations

A full round of creative generation or editing with three iterations of self-enhancement typically takes 3–5 minutes on

an NVIDIA L40 GPU using FLUX.1-dev1 and ControlNet for editing. The runtime is dependent on several factors such as prompt complexity, tool execution overhead and LLM inference time. Each agent uses GPT-4o (via API), which contributes significantly to latency, especially during multi-agent coordination and critique. In practice, the system is designed for rapid prototyping while maintaining high creativity scores. Early stopping is applied when the Creativity Index, $CI \geq 24$ for editing and $CI \geq 26$ for generation, minimizing unnecessary iterations. Optional user feedback can intervene between rounds for guided refinements. CI for editing and generation are chosen based on experimentation and can be adjusted according to user-preferences.



Figure 11. We explore how providing a negative prompt (ie “A normal <obj>”) affects generation using SDXL.

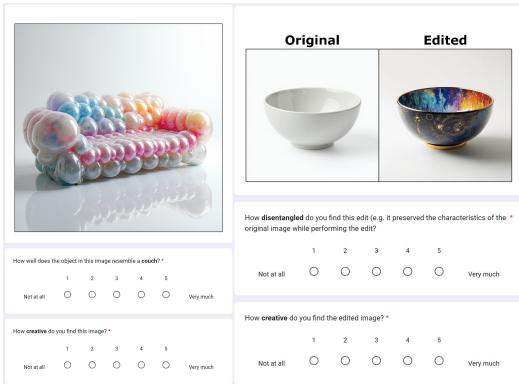


Figure 12. Here we show an example of questions asked in our user studies.

D. CREA Creative Image Synthesis Examples

D.1. Creative Image Generation

Creative image generation in CREA unfolds through a structured, collaborative multi-agent workflow composed of three key phases: Pre-Generation Planning, Image Generation, Self-Enhancement and Post-Generation Evaluation. Each phase involves distinct agent roles engaging in goal-driven dialogue to ideate, generate,

and refine creative imagery. We provide an illustrative example of the collaborative multi-agent debate for image generation using our proposed three-phase approach in the next sections. Note that the conversations are color-coded as follows: { ‘REASON’: ‘red’ , ‘THOUGHT’: ‘pink’ , ‘ACTION’: ‘green’ , ‘PROMPT’: ... }.

D.1.1. Pre-Generation Planning

In this phase, the agents collectively interpret the user-provided concept (e.g., “Couch”) and co-develop a high-creativity prompt. As shown in Figure 13, the Creative Director (A1) begins by synthesizing a creativity blueprint capturing the visual theme, style, constraints, and suggested associations—such as blending fantasy elements with recognizability. This blueprint is handed to the Prompt Architect (A2), who then generates six contrastive prompts, each aligned with a specific creativity principle (e.g., originality, aesthetic appeal, technical execution). These are merged via Chain-of-Thought reasoning into a single, richly structured prompt. The Generative Executor (A3) then verifies the technical feasibility of the prompt. This multi-agent back-and-forth ensures the final creative prompt is both imaginative and model-compatible before proceeding to image synthesis.

Image Generation

Once the prompt is finalized, the system transitions to image generation. As illustrated in the Figure 14, the Creative Director instructs the Generative Executor to generate an image based on the previously approved prompt. The Executor uses a text-to-image model (e.g., Flux) and executes a controlled synthesis by setting guidance parameters (such as CFG scale). The resulting image is then routed back to the Creative Director to confirm process completion. This phase emphasizes precise execution while preserving the conceptual richness embedded in the prompt, ensuring alignment between intent and output.

D.1.2. Post-Generation Evaluation

After the initial image is generated, it is evaluated in detail by the Art Critic (A4) and the Creative Director (A1) to determine its alignment with the intended creativity blueprint. As shown in Figure 15, the Art Critic applies a multimodal LLM-as-a-Judge framework to assign scores across six creativity principles—Originality, Expressiveness, Aesthetic Appeal, Technical Execution, Unexpected Associations, and Interpretability. Each criterion is scored on a 1–5 scale, and the total is aggregated into a Creativity Index (CI). The Creative Director then reviews these scores in light of the original intent and either approves the image or requests revisions if the CI falls below the creativity threshold. This phase ensures that the image undergoes a rigorous, objective-aligned critique before being finalized.

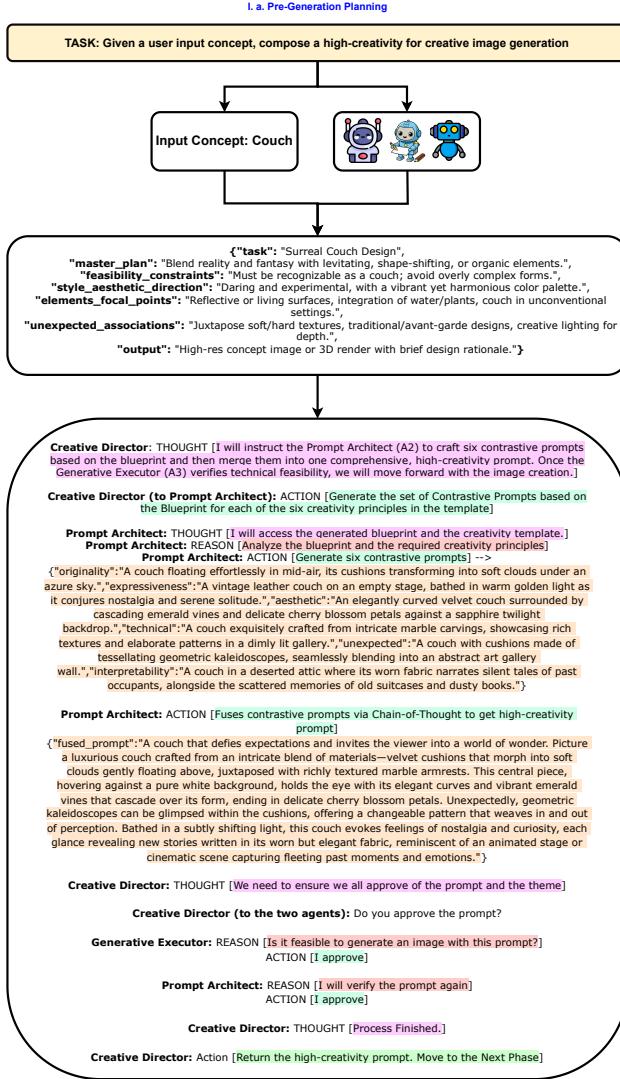


Figure 13. Pre-Generation Planning Phase

D.1.3. Self-Enhancement with Optional User-Guidance

If the image is deemed suboptimal, the Self-Enhancement phase is initiated to iteratively improve creative quality. As visualized in Figure 16, the Refinement Strategist (A5) interprets the Art Critic’s feedback to identify which creative principles scored poorly and formulates a targeted improvement plan. These suggestions are passed to the Prompt Architect (A2), who adjusts the original prompt by incorporating specific refinements (e.g., amplifying narrative elements or visual complexity). The Generative Executor (A3) then uses this revised prompt to regenerate the image. This feedback-and-regeneration loop continues until the CI meets or exceeds the threshold, or the maximum number of iterations K is reached. Through this iterative dialogue, CREA gradually enhances both the conceptual and visual

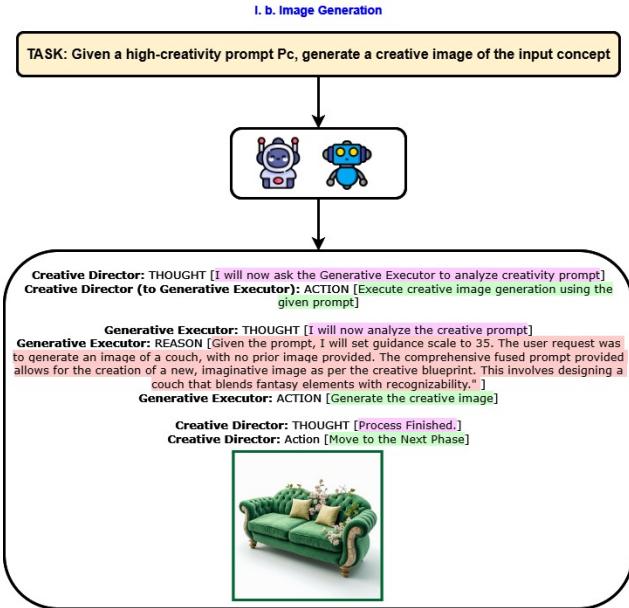


Figure 14. Image Generation by Generative Executor

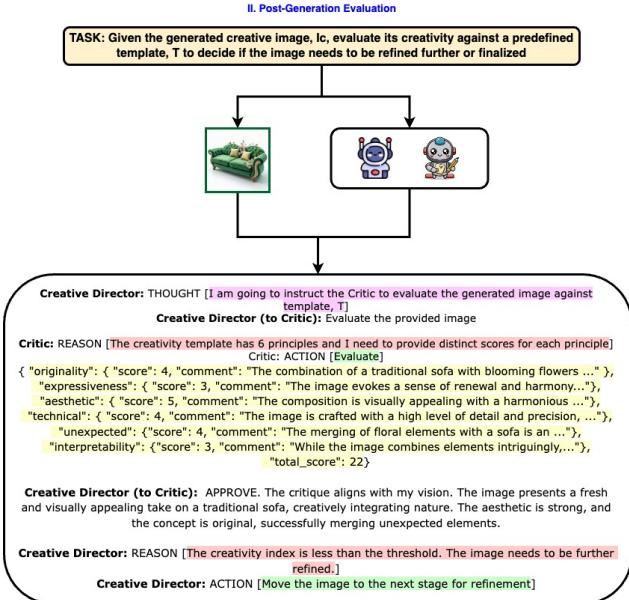
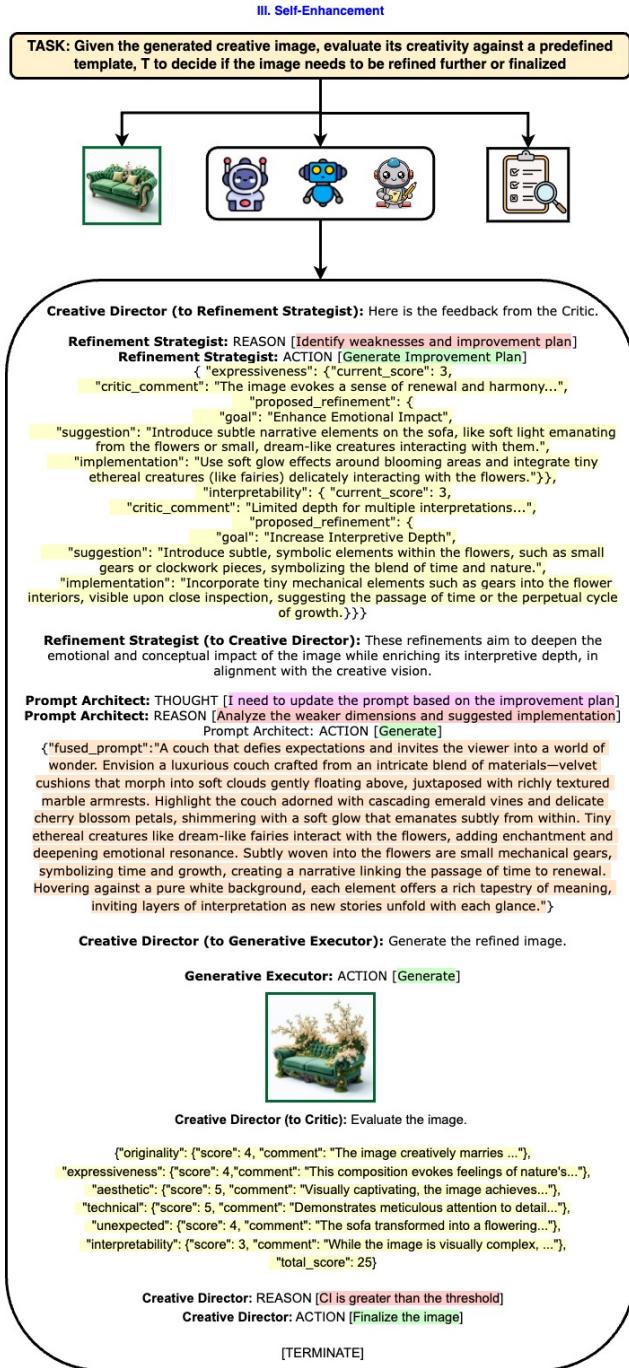


Figure 15. Image Generation by Generative Executor

quality of the image, converging on a final output that balances novelty, coherence, and artistic intent. The result is a highly creative nature-themed floral couch.

D.2. Creative Image Editing

Creative image editing in CREA follows the same multi-agent conversational structure as the generation pipeline but is adapted to operate on a user-provided input image. Instead of synthesizing a new image from scratch, the Gener-



ment. However, the Executor now conditions on the input image to preserve key visual elements while transforming its aesthetic, structure, or narrative creatively. Post-generation evaluation and self-enhancement phases remain identical, ensuring that the final edited image not only retains its semantic core but also meets the creativity threshold defined by the agent team.

E. Creative Video Generation

To demonstrate the versatility and extensibility of our agentic framework, we extend CREA to creative video generation. We conduct experiments using the CogVideoX [74] model as the generative backbone. This evaluation serves as a proof of concept for applying our multi-agent creativity principles beyond static imagery.

Instead of initializing the process with a static creative blueprint, our Creative Director agent generates a structured creative *video plan* containing key fields: **Subject**, **Action**, **Setting**, **Style**, and optional **Additional Details**. This plan is passed to the Prompt Architect, who composes a coherent and high-creativity video prompt via contrastive prompt fusion, similar to our image generation pipeline. The Generative Executor then synthesizes the video using CogVideoX.

As shown in Figure 8, our method produces significantly more imaginative and visually engaging results compared to baseline prompts such as “a creative object.”

F. Additional Qualitative Results

We provide various qualitative results for both generation and editing to demonstrate our method's ability to produce both diverse and highly creative images. Please see Figures 17-40.

Figure 16. Image Generation by Generative Executor

ative Executor (A3) applies disentangled edits using models like ControlNet, guided by a high-creativity prompt crafted during the pre-generation planning phase. The agents—Creative Director, Prompt Architect, Art Critic, and Refinement Strategist—engage in the same collaborative process of blueprint creation, evaluation, and refine-



Figure 17. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *couch*.



Figure 18. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *couch*.

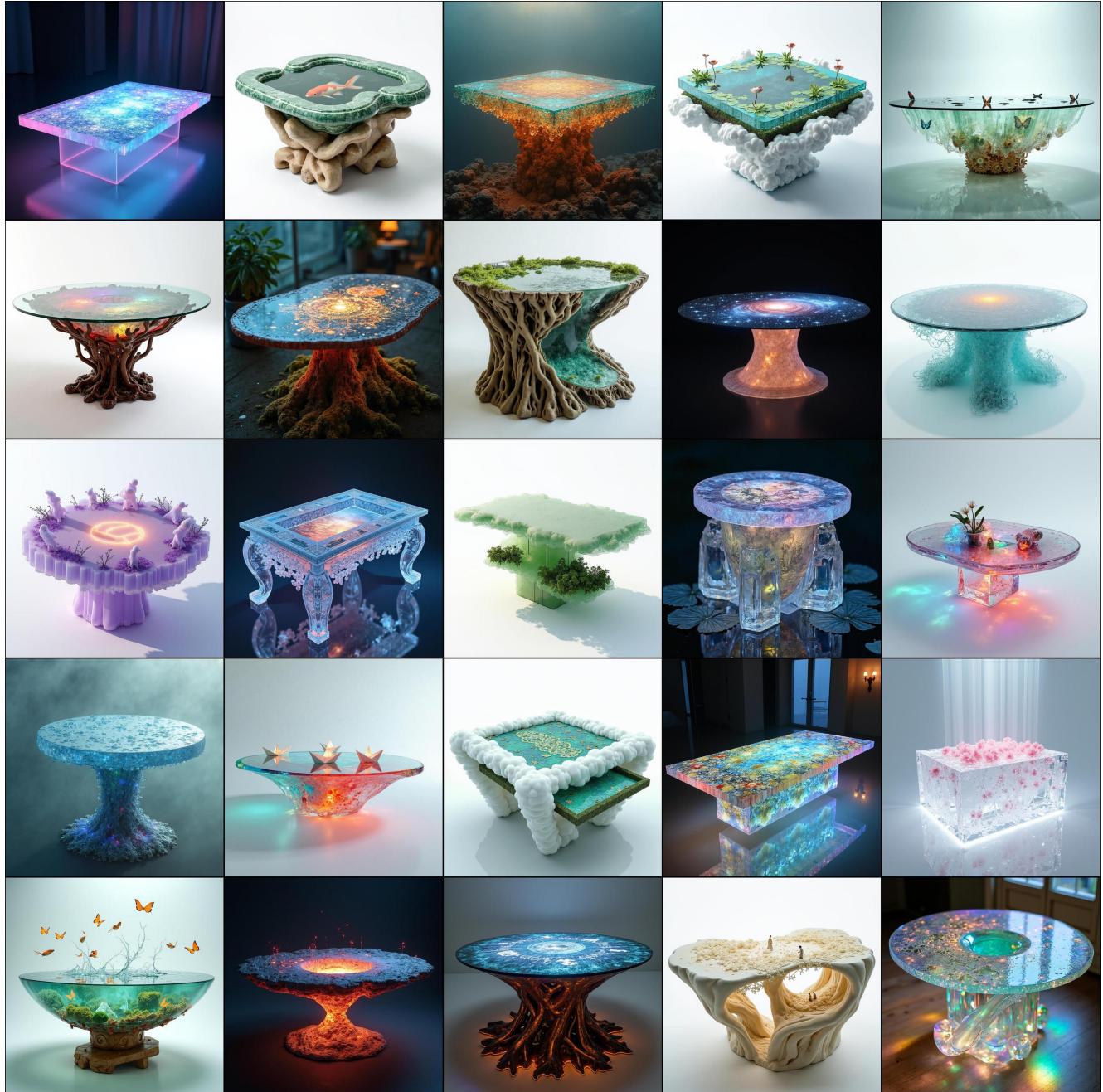


Figure 19. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *table*.

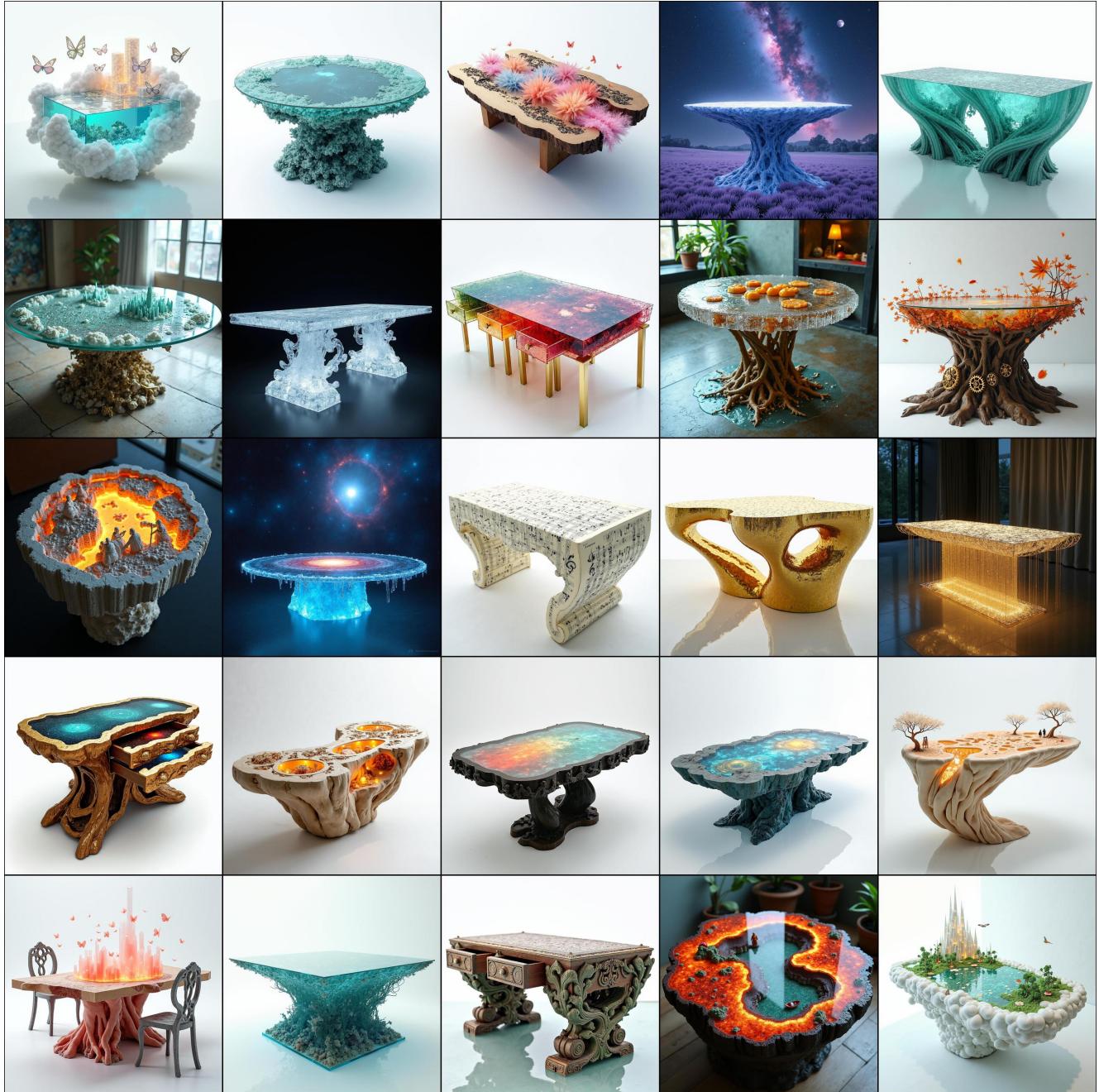


Figure 20. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *table*.

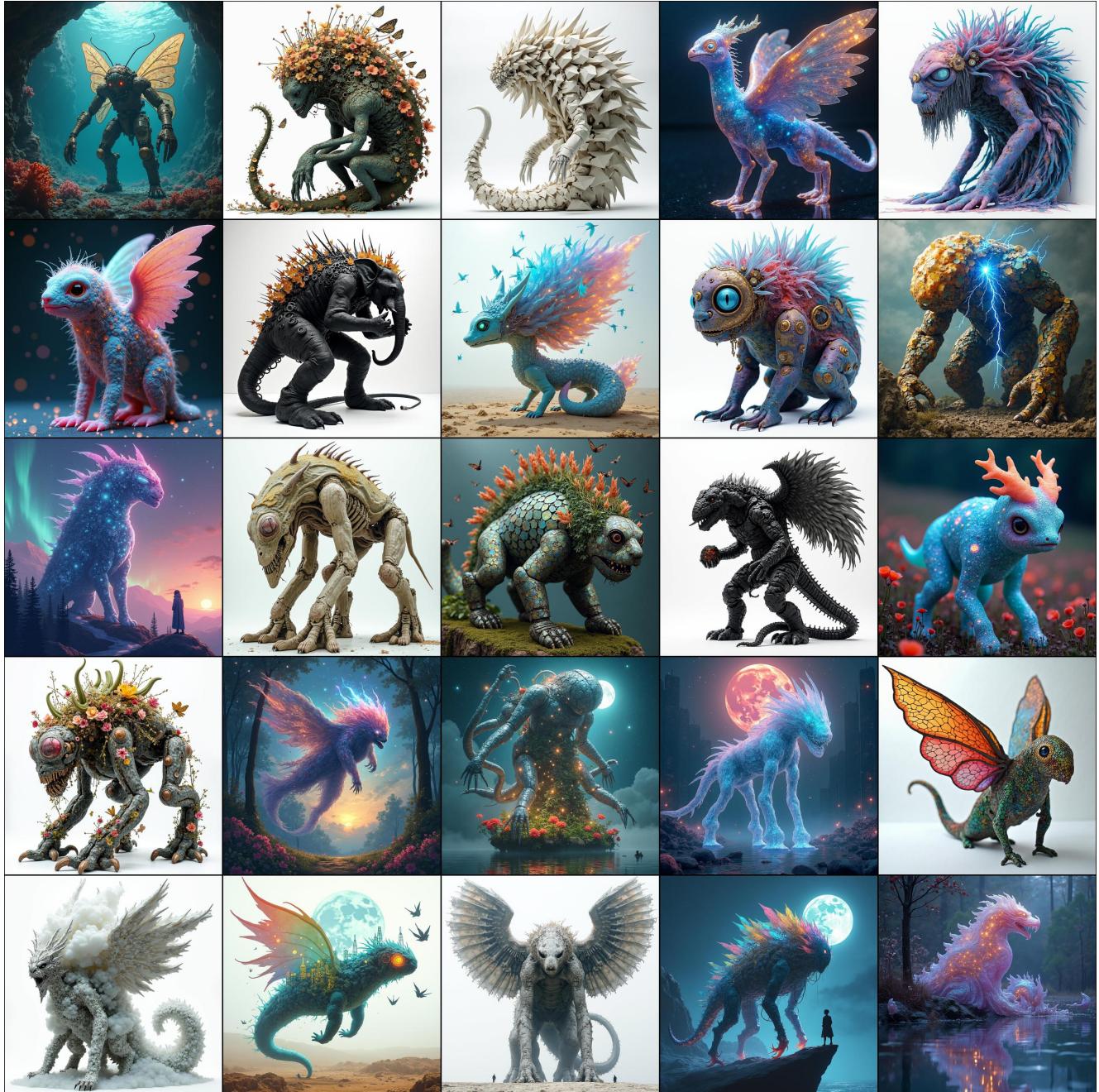


Figure 21. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *monster*.



Figure 22. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *monster*.



Figure 23. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *mug*.

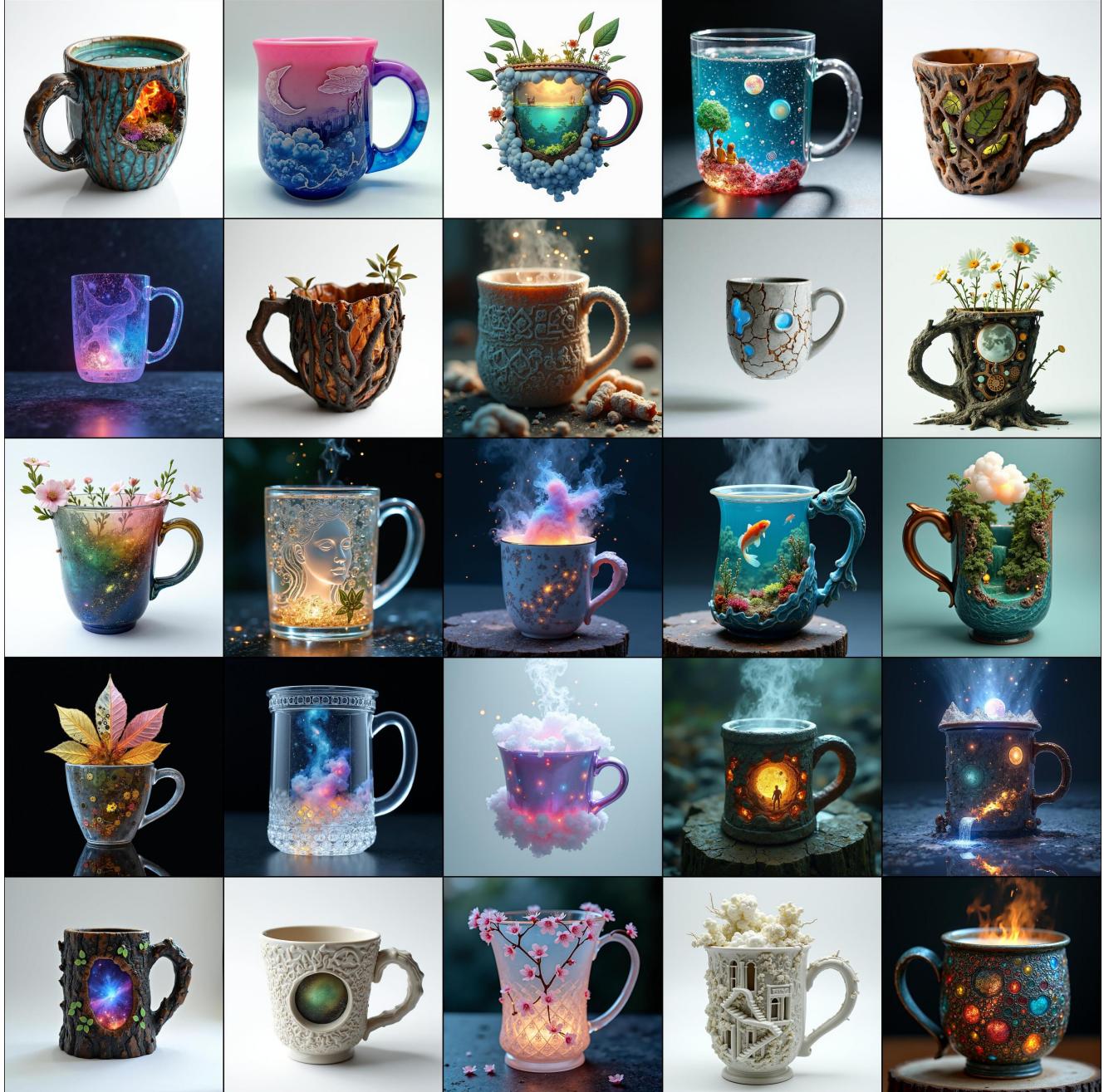


Figure 24. Generation results from CREA. We demonstrate that our method consistently outputs highly creative and diverse generations using concept *mug*.

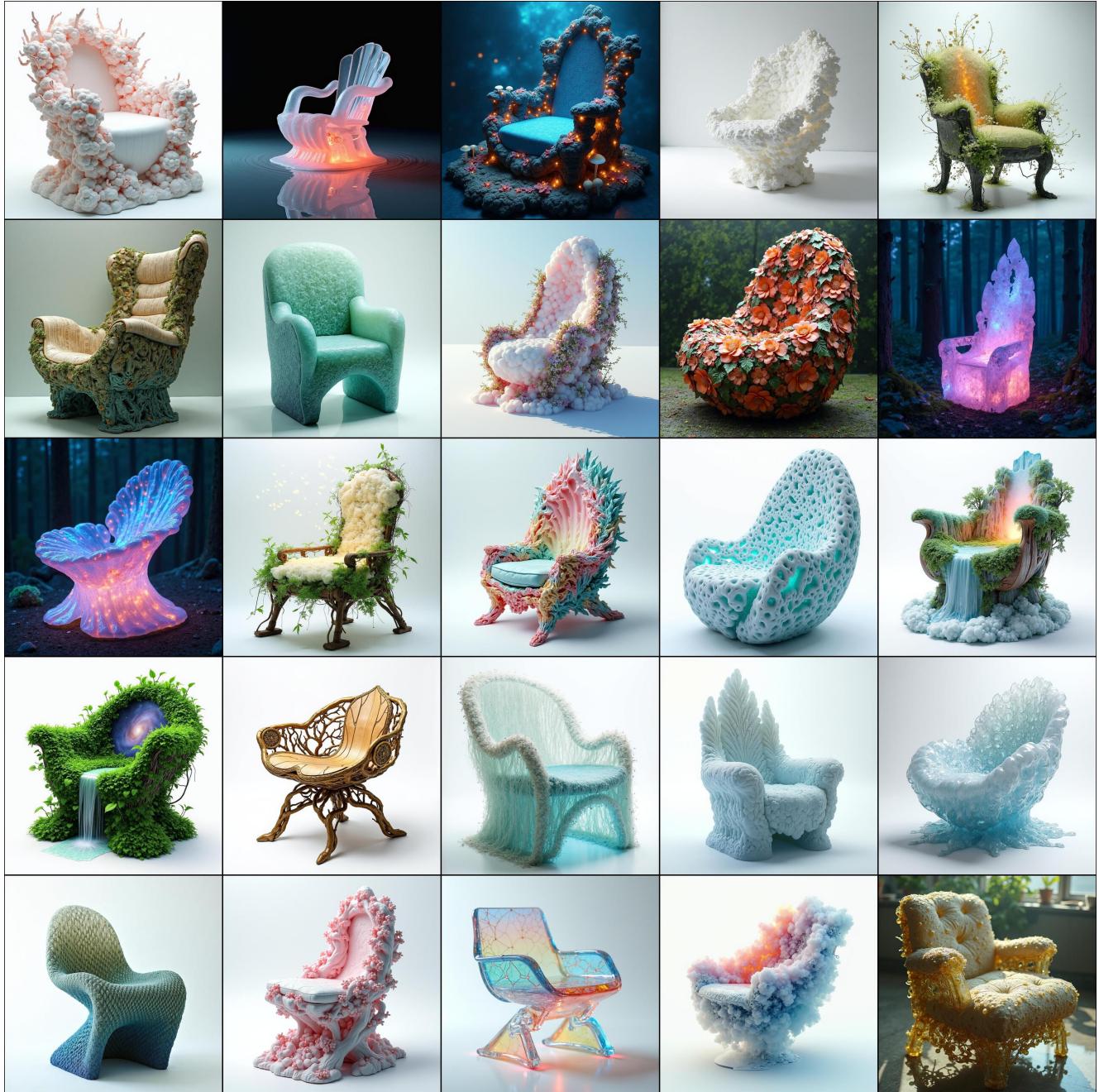


Figure 25. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *chair*.

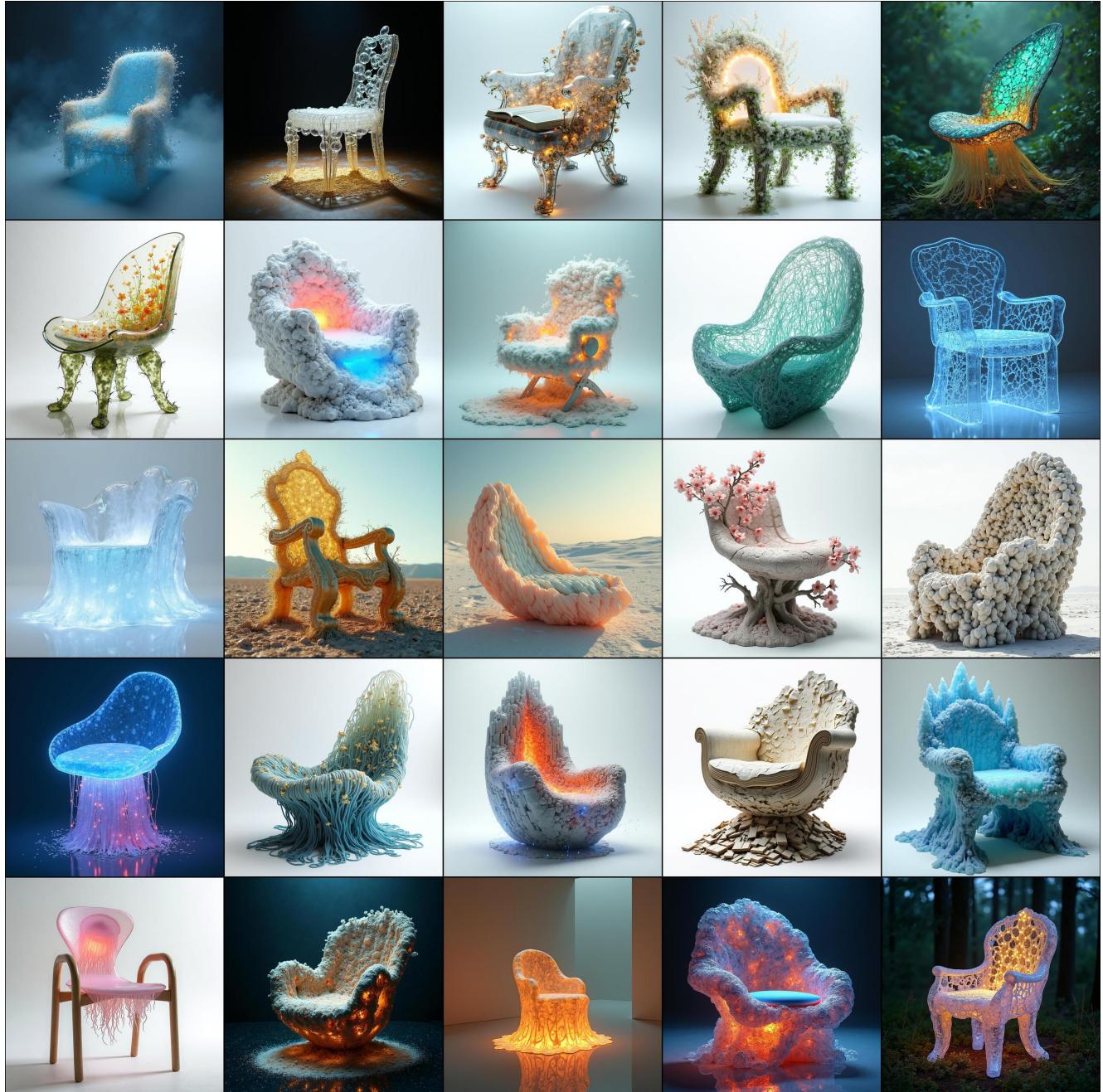


Figure 26. Generation results from CREA. We demonstrate that our method consistently outputs highly creative and diverse generations using concept *chair*.



Figure 27. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *car*.

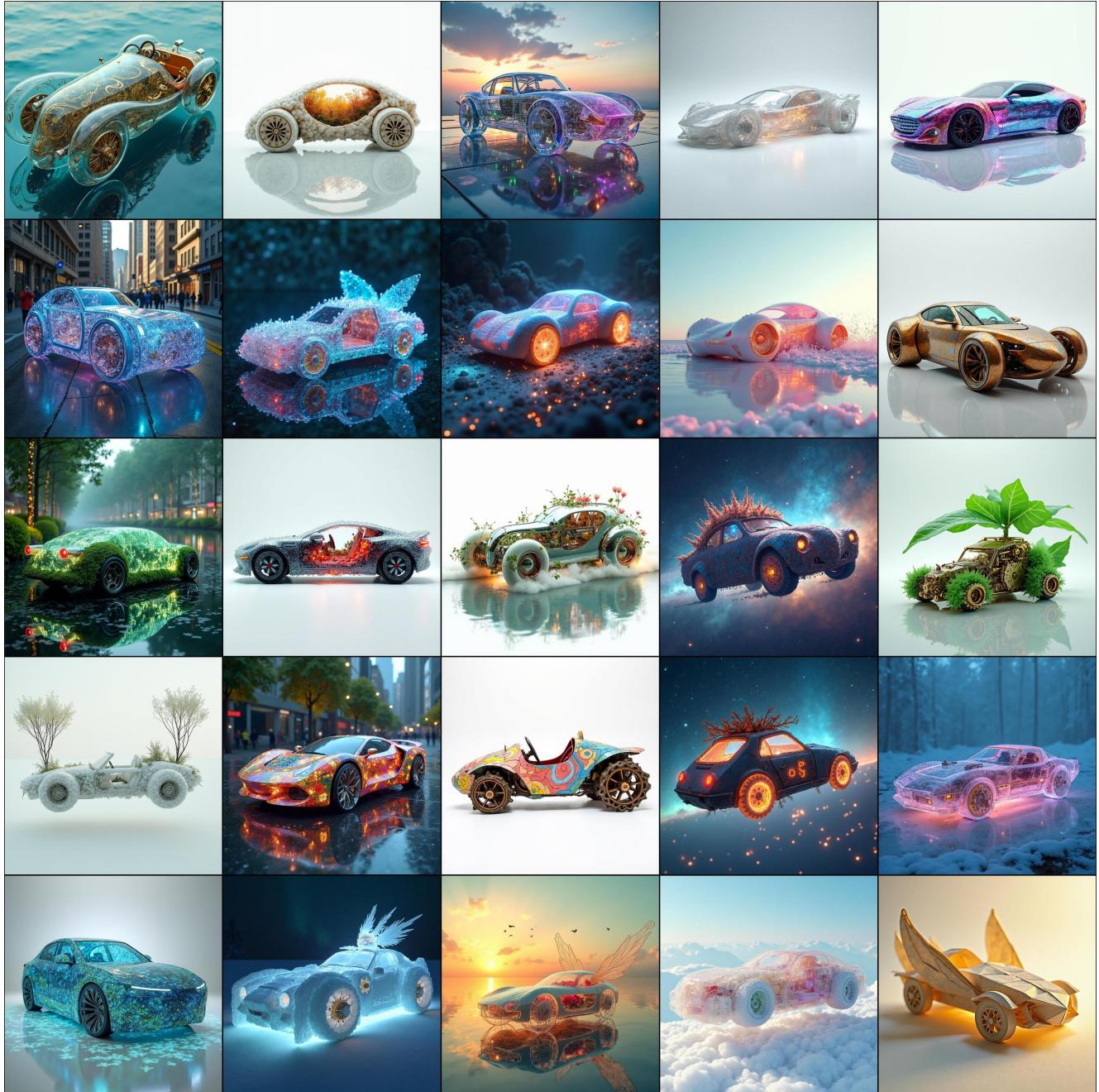


Figure 28. **Generation results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse generations using concept *car*.



Figure 29. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *bike*.



Figure 30. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *bike*.



Figure 31. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *table*.



Figure 32. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *table*.

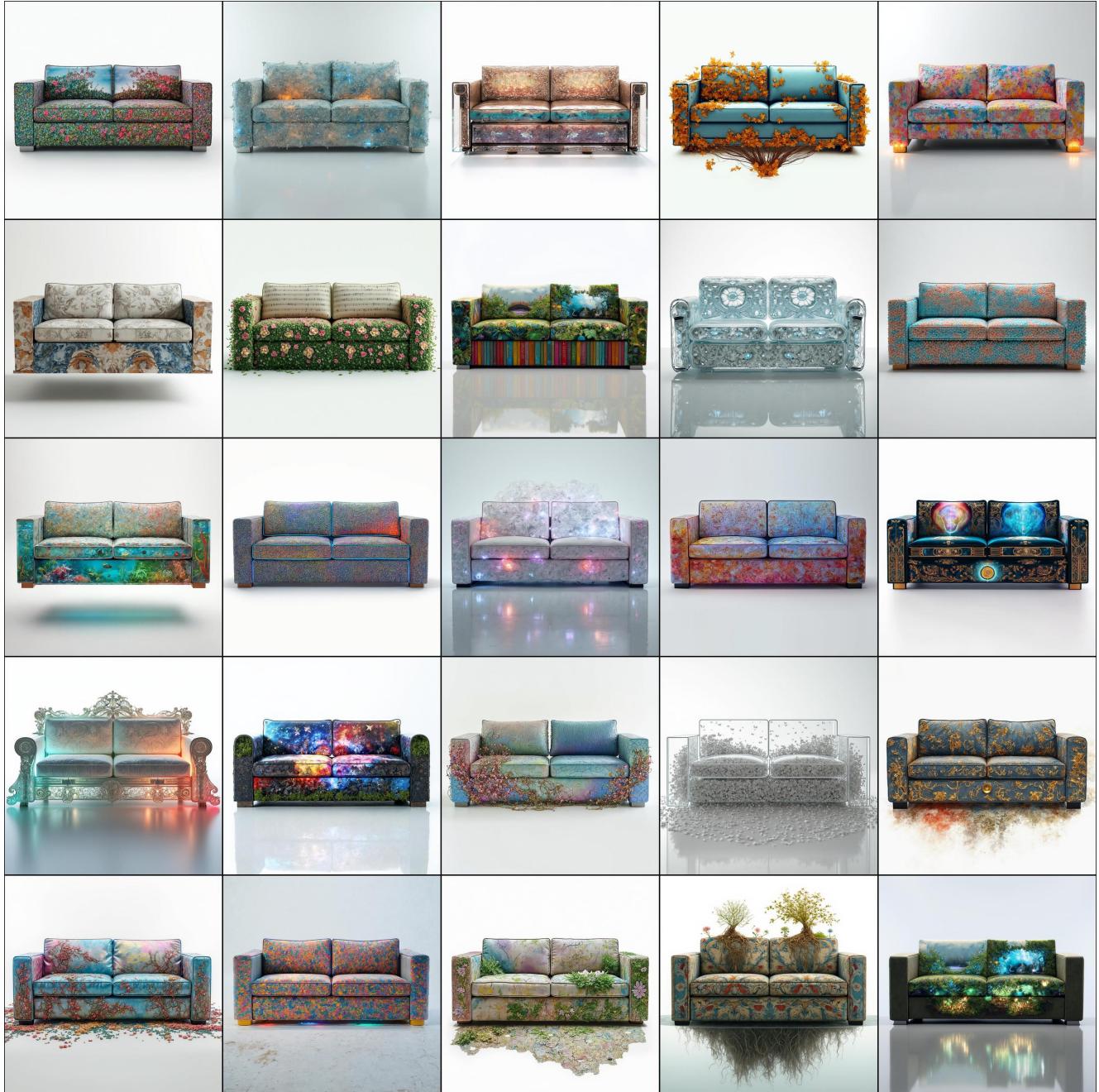


Figure 33. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *couch*.

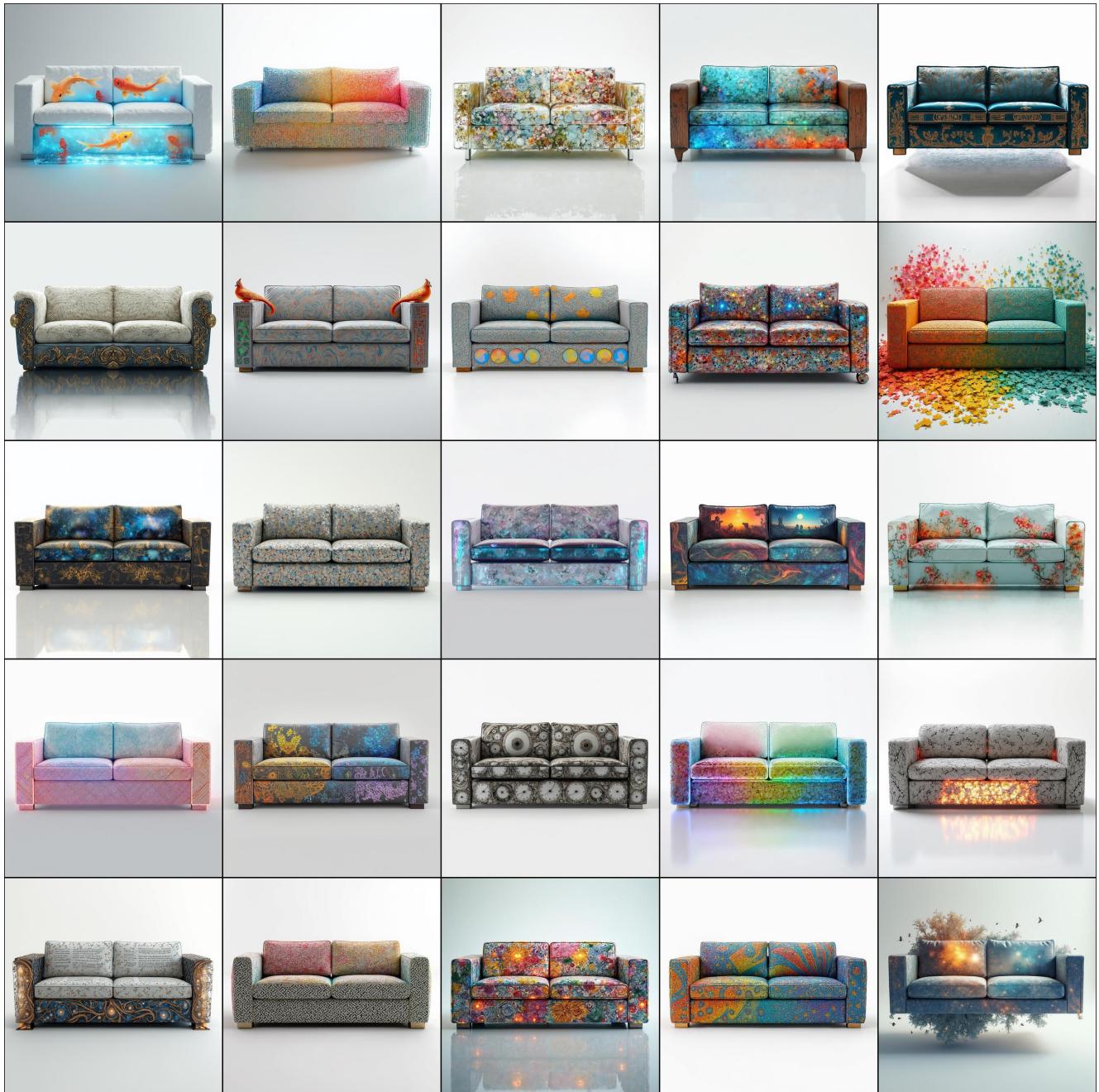


Figure 34. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *couch*.



Figure 35. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept bowl.



Figure 36. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept bowl.



Figure 37. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *helmet*.



Figure 38. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *helmet*.



Figure 39. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *guitar*.



Figure 40. **Editing results from CREA.** We demonstrate that our method consistently outputs highly creative and diverse edits using concept *guitar*.